An Investigation of Behavioural Systems Design and Social Dynamics in an Online Exercise Community

by

Daryl Leslie Foy

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Bachelor of Information Technology

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Declaration of Originality

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D L Foy

Abstract

The rising popularity of physical activity tracking devices and online social networks has seen them touted as potential tools to positively affect physical inactivity. These systems have found favour with a broad spectrum of users, from serious, competitive athletes to people trying to become more active, lose weight and boost wellbeing. To help determine their suitability to potentially assist with community health issues it's vital that we learn more about how they are used in practice, the exercise outcomes that accrue and how users relate with one another online. We need to understand how these systems are designed to target specific, positive exercise behaviours and determine how they might accommodate health behaviour change theories to act as agents of health change. The studies that comprise this thesis examine features of a population of users of an exercise tracking system known as *movescount.com* and the role the characteristics of these people and the design of the system may play in exercise outcomes and online interactions.

The first study involved an initial demographic and anthropometric analysis of the user population of the Suunto Movescount database of twenty thousand users. The results revealed users are predominantly male (89%) and list running as their main exercise (28%) with only 16% of them operating an external social media account. They were also quite lean with an average BMI (Body Mass Index) less than 25 and fit with a mean system-based Fitness Index Score of 5.7 (showing above average fitness). A classification and regression tree analysis was performed to find a group of attributes that classified users as persistent or non persistent. This work showed the fitter users used the system more frequently and of the least fit, those with an active Twitter account persisted with exercise for longer than their equivalent peers. Users with lower BMI scores and greater numbers of followers tended to login to the activity tracking system more often.

An examination of the system's equivalent to Facebook *likes* function revealed 75% of users positively self-affirmed their own exercise. Those that published their moves not only to the activity tracking system but also to Twitter persisted in using the system for longer, logging into the tracking system 13.2 more times and uploading their moves 5.1 times more than the average user.

The second study focused on the persuasive elements of the Suunto system. An online survey was administered to a subset of users of the system using questions to determine exercise status and device use. The survey incorporated a validated scale based on the Behaviour Change Support System (BCSS) theory, which was modified by incorporating two other standardised scales that measure relatedness to others in offline physical activity (ROPAS), (Lehto et al., 2012) and the online sociability sub scale of the Brief Test of Online Behaviour (BTOB) by (Johnson & Kulpa, 2007. A factorial analysis of the results found the intention to continue using the system was determined by the users' perceptions of the effectiveness of the system, the effort required to use the system, the credibility of the system and the social support offered by the system. It was also revealed that any individual who perceives high levels of relatedness to others during physical activity in the real world and identifies strongly with the online community of fellow digital exercise system users will likely feel they receive high levels of social support from the system, thereby positively affecting their use of the system. Structural equation modelling shows that an increase in age and being single brings statistically significantly lower ROPAS. This implies that as users age and live as singles their relatedness to others in physical activity declines and with it a propensity to engage with the systems social support functions may follow.

The third study engaged a panel of five experts experienced in the theoretical aspects and practical application of BCSS to the design, development and deployment of health behaviour change systems to complete an independent evaluation of the Suunto *movescount* system. They found that the system rates strongly for primary task support and social support but only satisfactory for systems dialogue and credibility. The panellists also indicated it was deficient in Reminders and Suggestions, design cues regarded as crucial for persuasiveness in apps. Further, the lack of adequate Simulation and Rehearsal functions may impinge on the planning and execution of user exercise; (Holmes & Calmels, 2008). The panel found the system lacked in ideal levels of praise and reward for user exercise efforts, a feature considered important in health apps design; (Baranowski, Thompson, Buday, Lu, & Baranowski, 2010; Thompson et al., 2010) A recommendation from these findings is that product development teams engage with behavioural scientists during the development phase to make best use of health behaviour change and persuasive systems practices.

The final study investigated if individuals who tweet their exercise efforts from the *movescount.com* system exercised differently according to their online social influence. A quantitative analysis of a sample of such users was conducted. This determined if there was anything out of the ordinary by way of exercise volume, frequency and type and whether or not an independent measure of their online social influence furbished by the KLOUT.com service could reveal if those who scored highly There was no relationship between exercise session duration or intensity and online social influence.

The thesis identifies an activity tracking system as an effective technology for persuading individuals to maintain exercise behaviour. It has identified that those users that score highly on a measure of relatedness to others in physical activity in the real world and identify strongly with the online community of peers will indicate they receive high levels of social support from the system and are more likely to continue using the system for longer. These findings may have implications for designers of activity tracking systems through the inclusion and exclusion of social networking functions by user profile as determined by a programmatic operationalization of the validated scale created by this thesis.

Keywords: relatedness, persuasive, activity tracking, social networking, klout, ROPAS, BCSS, self-affirmation, self-determination.

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Chapter One

Introduction and thesis overview

The global market for wearable sensors and their integrated online and mobile-based software ecosystems is growing explosively, with numbers expected to hit 485 million by 2018, (Vickey, 2014). Around one in ten people over the age of eighteen in the U.S owns a wearable fitness device, ((Ledger & McCaffrey, 2014). An evidence base that provides dispassionate evaluation of the design, use and broader sociological, psychological, and physiological contexts and effects of the technology; lags. Little is known of how these systems are designed to encourage or persuade individuals to commence, maintain or increase exercise behaviour. Similarly, there is a dearth of evidence that shows the operationalization of established health behaviour change theories in these systems to any large extent. However, research momentum is gathering and the mechanics and utility of persuasive systems design for health and wellbeing are being actively investigated. Kelders, Kok, Ossebaard, & Van Gemert-Pijnen (2012) in a systematic review of web-based health interventions, found that differences in technology design incorporating persuasive design elements help predict adherence to interventions. Incorporating persuasive design principles into health information systems for rural women in India has altered existing social beliefs and positively influenced the adoption of health practices, (Parmar, Keyson, & De Bont, 2009).

From recent research (Kernot, Olds, Lewis, & Maher, 2013), it is implied that the technology may play a powerful potential role in encouraging the commencement and continuation of exercise behaviour (Maher et al., 2014) and (Vandelanotte et al., 2014). How and why this association works and how it can be optimised are questions that remain to be answered and have provided the impetus to this thesis.

This study is also justified given the size of the market, the growing adoption of some elements of a health behaviour change model by many of these technologies in general; (Lyons, Lewis, Mayrsohn, & Rowland, 2014), explosive growth in the number of related apps (Middelweerd, Mollee, van der Wal, Brug, & te Velde, 2014), and the potential utility for self-monitoring of health and well-being interventions (Swan, 2012).

From the literature, a number of consistent findings emerge that are germane to the goals of this thesis. These span health behaviour change theories, emerging persuasive systems design models and exercise adherence research, from which can be drawn an investigative framework to understand how digital exercise technology is used in free-living populations with particular focus on the role of social factors. Health behaviour models provide a means for understanding and measuring exerciser motivation and associative factors as they affect individual and group exercise behaviour. In examining those factors that affect the motivation of an individual to exercise on a regular basis, the satisfaction of the three basic psychological needs of autonomy, competence, and relatedness to others as espoused by the Self Determination Theory (SDT) have consistently proven to be instrumental in the enactment of this behaviour (Bailey & McLaren, 2005;Gunnell, Crocker, Mack, Wilson, & Zumbo, 2014; Solberg, Halvari, Ommundsen, & Hopkins, 2014; Springer, Lamborn, & Pollard, 2013; Wilson, Rodgers, Blanchard, & Gessell, 2003).

The presence and support of other people that an individual can relate to, most often expressed as *social support*, is identified as a recurrent predictor of exercise adherence in most studies of intervention effectiveness in general healthy adult populations, (Gibbison & Johnson, 2012; Sherwood & Jeffery, 2000; Oka, King, & Young, 1995; Rees & Hardy, 2004) as well as in groups of adults recovering from and managing chronic disease, (Martin & Woods, 2012; Moore, Moore, & Murphy, 2011). This pattern of positive social support assisting exercise adherence, long established in offline free-living populations, is now beginning to be reflected in the online social networks of exercisers that allow publication of individual physical activity data from tracking devices, (Pagoto, Schneider, Oleski, Smith, & Bauman, 2014; Pagoto et al., 2014).

The fusion of established health behaviour change theories and the design and use of digital exercise tracking systems for regular exercise draw the focus of the current study. In many ways, systems designers and health behaviour change practitioners are playing catch-up with the power and pervasiveness of wearable sensors and online social networks and may need to consider closer co-operation with one another to improve the efficacy of the technology for exercise uptake and adherence. Progress is being made in the development of substantive theoretical frameworks that assist in the design and development of systems that can persuade users to engage in targeted behaviours such as exercise commencement and maintenance (Oinas-Kukkonen & Harjumaa, 2009; Sundar, Bellur, & Jia, 2012). It should be noted that (Sundar et al., 2012) espoused a model that insists the incorporation of systems functions that encourage interactivity with other users of common interest will improve the potential for increased relatedness of users. This raises the question of the transference, if any, between an individual's offline relatedness to others in physical activity to their use of the online social networks that manage their uploaded physical activity data.

How does it relate to their use of the device and their online social interactions? Answers to this question lie at the heart of the rationale for this thesis.

The Behaviour Change Systems Support (BCSS) and Persuasive Systems Design (PSD) work of (Oinas-Kukkonen et al., 2009) is the most advanced of the emerging systems-based behaviour change theories. It has devised and validated instruments of measurement and generated a body of knowledge that stems from the use of the theory in a multitude of persuasive systems applications. BCSS postulates that the inclusion of categories of design features explained by the theory organised under primary task support, dialogue, support, systems credibility, and social support may assist in increasing the *persuasiveness* of a technology design. Persuasiveness is a term growing in acceptance to describe how elements of hardware and software design may serve to influence an individual's behaviour. It is most commonly applied to problems of health behaviour and energy usage that are addressed using technology. The social support category comprises systems features that map neatly with conventional elements of behaviour change theories and have been shown to be influential in yielding persuasiveness (Stibe, 2014 ;Stibe & Oinas-Kukkonen, 2014).

Exactly how these persuasive social support features may affect user exercise behaviour in a widely adopted system, how easy or difficult the user finds the system to use as a consequence of the implementation of these features, how persuaded they are to continue to use the system, and whether or not it affects their exercise behaviour are amongst questions this thesis seek to address. Designing a suitable methodology for guiding the study is aided by the technology under investigation. Online social networks provide the data management infrastructure that deliver scale, measurement, structural control, replication ease, and behavioural fidelity, all significant advantages over traditional controlled trial designs, (Centola, 2010). Popular physical activity tracking systems such as *FitBit*® and Suunto *Movescount*® incorporate functionality that enable their users to share exercise goals, plans, and actual uploaded exercise sessions in a closed social network facilitating sharing of their exercise information and activities and online social interaction around this. A cross section of the core features of the *Movescount*® based on screen shots is provided in Appendix G.

Thesis Goals

The overarching objective of the thesis is to apply the theoretical frameworks of Self Determination Theory (SDT) and Behaviour Change Support Systems (BCSS) to a unique, proprietary, large and complex data set of free-living fitness device users. This approach seeks to develop insights for establishing more effective systems design features that incorporate social media components capable of persuading individuals to persist in their use of activity trackers for positive exercise behaviour. This approach is expressed in terms of six goals, which guide the investigative methods used. The diagram below depicts the relationship between the thesis goals. The subsequent table then traces the expression of these goals through lower level research questions into the studies completed to answer them.

Goal One

To determine the nature and extent of associations between a user's demographic and anthropometric characteristics, their social interactions and exercise behaviour.

Goal Two

To identify the attributes of users who show the greatest persistence in using the device over the period of data collection used for analysis.

Goal Thee

To survey a sample of this population using standardised scales to identify and determine the user’s pre-existing exercise behaviour prior to device purchase and their intent to continue using the system.

Goal Four

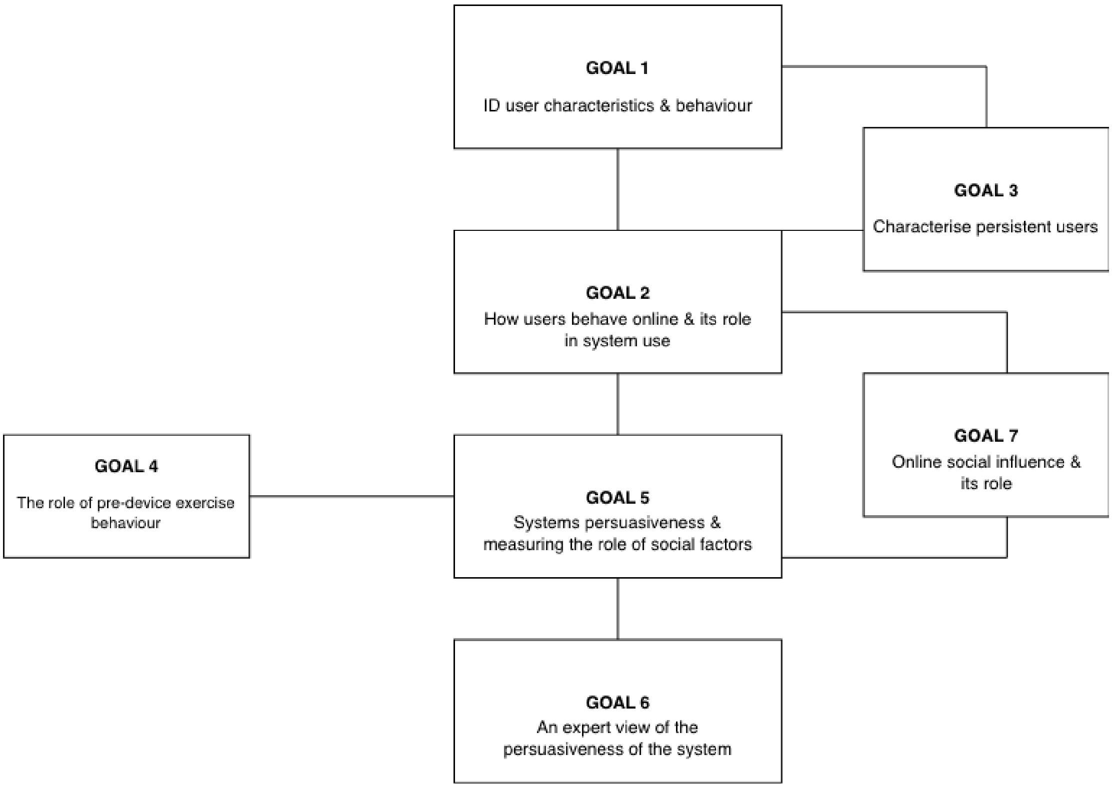
To gain a thorough understanding of the persuasiveness of the system in positively affecting its persistent use for exercise by testing existing measurement scales, creating a structural model and validating a new scale focused on the social elements of systems persuasion.

Goal Five

To canvass expert views on the PSD-based persuasiveness of the activity tracking system being used to determine how compliant the system is with the idealized MSD model’s feature coverage.

Goal Six

To determine any association between an individual’s online social influence and their exercise outcomes as published by users of an activity tracking system to Twitter.



Overview Figure 1 The Connectedness of Thesis Goals. Copyright© D.L.Foy 2016.

This thesis differentiates itself from the existing knowledge base and concurrent external projects that are underway through its use of a ratified live database of 20,000 users of the Suunto movescount system. By creating a new measurement scale that combines existing validated scales for BCSS-PSD plus new additions of scales for online sociability (O_SOC) and ROPAS, this study aims to provide a new means for determining the association between how an individual perceives their relatedness to others in real-world physical activity and their use of the online social networking features of activity tracking systems. This may allow us to better underastand how the social networking functions of an activity tracking system affects its continued use. Identifying a subset of users from within the population sample who opt to publish their uploaded exercise sessions to the Twitter social network provides us with a new user type with discernible behaviours in terms of exercise and online sociability that comes under empirical scrutiny for the first time.

Realisation of some or all of thesis goals, will yield valuable insights that help us better understand the characteristics of users of digital exercise tracking systems, how they interact with these systems, and most importantly, how persuasive systems design elements influence systems use. . This should provide opportunities for health behaviouralists and software designers to apply knowledge from the study to improve persistent use of the technology for positive exercise behaviour.

The methods used in the study include a balanced approach between quantitative and qualitative techniques. They offer other researchers a ready to use toolset for extending the research into other populations and different persuasive systems.The population dataset from Suunto Oy, once it has been transformed, validated, and modelled using SQL programming, will be subjected to scrutiny using descriptive statistics to help understand the nature of the system's users and how they interact with the system. Multiple regression analyses will help establish associations between key variables around user characteristics, exercise behaviour, exercise outcomes and online social activity using the system. To establish an insight into persistence with the device over time, CART analysis (Breiman, Friedman, Olshen, & Stone, 1984) and binomial regression techniques will be employed. Following a quantitative analysis study members of the vendor's health research opted-in database will be surveyed using online survey management systems *So-Go*® and qualitative techniques employed spanning descriptive and multiple regression techniques. To better assess the persuasiveness of the Suunto activity tracking system, a panel of experts experienced in the application of BCSS-PSD will be recruited to complete a previously used mechanism for recording assessments and these assessments subsequently analysed using qualitative techniques. Finally, quantitiative techniques will be used to identify any association between the tweeting of exercise activity through *movescount.com* by users, their online social influence and exercise ouctomes.

The study represents a rare chance to investigate the attributes and dynamics of a free-living population using exercise wearables that enable exercise behaviour and social interaction for their users. This affords the investigator a less controlled circumstance to analyse and understand a large group of individuals than is afforded by more common small controlled trials and simple online recruitment models. Although the data for the thesis come from a particular fitness device, empirical results from the data using the work of (Oinas-Kukkonen et al., 2009) should be fairly generalizable, as their structural equation model focuses on general characteristics such as ease of use and perceived reliability and expertise. By supplementing previous structural equation modeling with the constructs related to sociability and social interactions with others through exercise, the present research extends the extant empirical literature in BCSS. For the third study, identifying and recruiting sufficient academic experts proficient with BCSS-PSD, its applications, and instruments was difficult given the embryonic development of the model and the limited population of its proponents. The relatively small sample size of expert opinions may bias the results towards more variability in opinion than would be true of a larger population of experts. It does nonetheless serve an important purpose as a counterpoint or sanity check for study two.

Given the breadth of coverage of the studies in the thesis, the following content roadmap is provided.

Chapter Two is a **literature review** of theories undertaken to determine a theoretical framework for examining the role of health behaviour models and their social support constructs in digital exercise tracking systems. These models underpin the use of digital exercise devices and span health behaviour, persuasive systems design, social network structures and social media and adherence to exercise. This chapter has a synopsis of the main streams of theoretical evidence encapsulated at the start of each subsection in a summary table

Chapter Three provides a detailed précis of the **methodology** used to design the analytical portion of the thesis and attain meaningful results. Each study component completed is outlined with details of the specific research questions asked for each and the specific measurement instruments used to guide analyses. An explanation of the origins, transformation and management of all data source files is given. The content provided also guides the reader through the process of methodology choice, evolution of study choices as a result of the initial findings from study one. Implementation of the methods, from research question elicitation through to cohort recruitment, device selection and application is discussed.

Chapters Four through to Seven frame the **results** attained by application of the study methodology from the data sources. Quantitative analyses including standard descriptive statistics and quantitative techniques: multiple regressions, probit regressions, CART and negative binomial regressions are used to derive findings. Additionally, qualitative techniques answer questions particular to studies two and three. Study two is primarily uses structural equation modelling to evolve a new measurement scale to assess the relationships between social connectedness in real world physical activity with online social interactions, exercise behaviour and systems use.

Chapter Eight uses the results from the previous chapters to formulate a balanced **discussion of the findings** in the light of the literature and evidence identified in Chapter **Two**. It identifies the assumptions, limitations and delimitations that limit the scope and applicability of the research processes and output.

Chapter Nine draws a line under the key learning derived from the investigation and considers what may be of value to the base of knowledge and **possible future research opportunities** related to the findings. It also references a treatment of the Implications for Design section in Appendix L that explains thesis findings that may be translatable for designers of activity tracking apps.

The **Appendices** includes larger data analysis tables and intermediate computations from Study One, source code for the original MySQL programming done to the population dataset to vouch safe its validity and integrity. It also provides the relevant ethics paperwork, survey forms and invitations necessary to engage with the cohorts. A small compendium of key functions and features of the movescount.com system used is provided here as the exemplar activity tracking system upon which the research works is based.

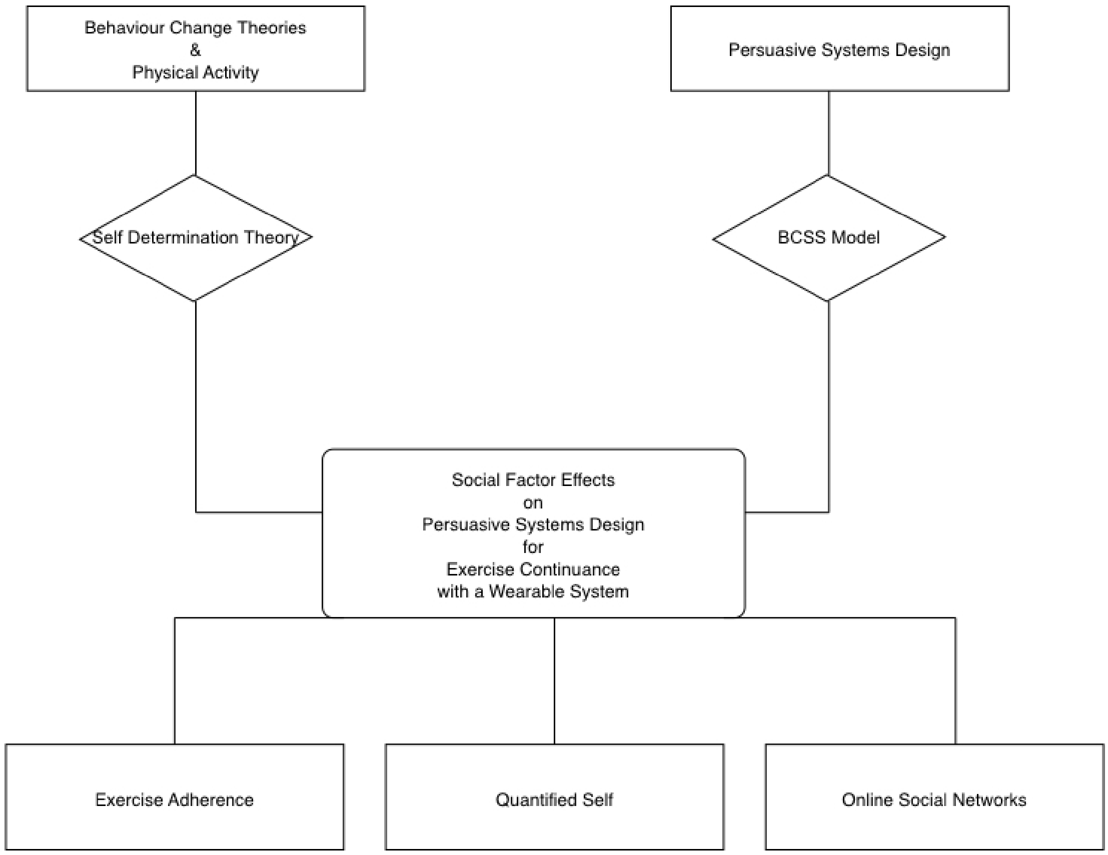
Chapter Two

Literature Review

Introduction

To understand how behavioural systems design and online social dynamics affect the use of an activity tracking system necessitates the review of a number of discreet areas of research. This need directs our attention to mainstream health behaviour change (HBC) theories with specific focus on the Self Determination Theory (SDT) and its role in physical activity interventions. It also means investigating the role of nascent persuasive systems design (PSD) models, in particular the Behaviour Change Support Systems (BCSS) model and their role in shaping technology that mediates positive behaviour change including exercise. As the thesis looks to cast light on the bridging of online and offline social behaviours for physical activity then emerging research into online social network (OSN) design and its part in information diffusion for positive behaviours is examined in depth. Similarly, it’s crucial we identify the role of real world social factors that affect the adherence of individuals to long-term exercise interventions if we are to better marry the potential of apps and wearable technology with conventional approaches that have shown to be crucial to success in maintaining long-term exercise behaviour.

The literature review provides a context for the study and a guide for the data analyses essential to this project as shown in Figure (i).



Overview Figure 2 Overview of Literature Review Areas Investigated for Study. Copyright© D.L.Foy (2016).

This approach was used to review the available evidence in the literature and to shape the analytic direction, content and techniques used in the data interrogation phase. It guides the modelling of those items of interest that may help to bridge the gap between behavioural change theories and persuasive systems design.

Rationale for Inclusion and Exclusion of Literature

The literature content was seleced to best understand and apply a subset of tenets from existing theories and models to the problem space under study which is nascent and undergoing formalisation. Their interrelationships are depicted in the diagram. This information analysis is used to identify potential means for the improvement of activity tracking systems design that may contribute to persistent exercise behaviour using the technology. It is reasoned that examining and understanding the applicability of substantiated behaviour change theories is a sound starting point. The Self -Determination Theory (SDT), (Brötz, 2013) and Social Cognitive Model (SCM), (Young, Plotnikoff, Collins, Callister, & Morgan, 2014) are highly regarded, substantially validated and in common use for exercise interventions. Both are also being used in part to help design lifestyle intervention apps for health behaviour change; (Payne, Lister, West, & Bernhardt, 2015).

As depicted in the diagram the nascent persuasive systems design models such as Sundar's Motivational Technology Model (Lee, Lee, & Hwang, 2015), Fogg's Behavioural Model (Fogg, 2009) and the Behavioural Change Support System (Oinas-Kukkonnen, 2009) are included as they have partial roots in the older mainstream theories. These new models are used to develop activity-tracking systems. This link is most evident in the mapping of user motivation and social support functionality as a positive mechanism for persisting with exercise; both SDT and SCM have a rich evidence base that articulate and validate the salience of these attributes.

The Transtheoretical Model (or Stage of Change), (Sporakowski, Prochaska, & DiClemente, 1986) is another popular behaviour change approach used in health and physical activity that was considered for inclusion in the review. However, it lacks the needed links from its basic tenets to the emerging persuasive systems design models and hence were not included in the literature review.

Because a majority of the activity tracking systems such as the *movescount.com* app used for the purposes of this thesis utilise online social networks (OSN) and self-monitoring technology (Quantified Self), investigation of their literature is seen as essential to formulate a framework of understanding for the thesis.

The OSN is used by *movescount.com* and similar systems to encourage purchase then continued use of the technology for exercise. Without knowledge of this evidence it would be impossible to identify which investigative methods and devices to use in order to pinpoint areas of design improvement that may aggrandize device use for persistent exercise. For example, which elements of OSN have been shown to be positively associated with improved exercise behaviour?

A detailed treatment of exercise adherence in general and its support via technology in particular is considered essential to the planned outcomes from the thesis. If an overriding objective of public health policy is to encourage sustained physical activity it places the onus on researchers that evaluate and produce activity tracking systems to understand the principles and practices of successful exercise adherence strategies that pre-date the current generation of technology. It's in everybody's interest that individuals use the devices where applicable for as long as possible to sustain exercise.

A planned outcome of this thesis is to demonstrate the importance of capitalizing on existing evidence and theoretical frameworks as an entry into designing new means for improving the persuasiveness of activity tracking systems so they can support their persistent use for positive exercise behaviour.

The following literature review provides a detailed insight into the identified areas of research considered essential to realising the goals for this thesis.

Health Behaviour Change Theoretical Models

The following table summarises the main studies, their investigative topics and resultant findings for this research area.

Mainstream Behavioural Change Theories and Exercise

Table 1. *Summary of Literature Review for Behavioural Change Models and Exercise*

Study	Topic	Finding
Michie et al., (2009)	Physical activity and healthy eating interventions.	The most efficacious of these capitalised on specific implementations of behavioural change theory elements, in particular goal setting, feedback and self-monitoring of behaviour.
McAuley et al.,(2003)	Exercise adherence in adult T2DM patients	Exercise participants are more likely to adhere to prescriptive programs if they enjoy task mastery and competence along with autonomous motivation.
Tudor-Locke (2004)	Group exercise	Exercising together can also motivate individuals to do more activity; people increase their activity level as they engage in light competition.
Rovniak et al. (2002)	Social support influences physical activity through its effects on self-efficacy.	Social support influenced physical activity through its effect on self-efficacy and self-efficacy in turn through its effect on self-regulation (goals and plans).
Stanley, Cumming, Standage, & Duda (2012)	Exercise imagery & autonomous motivation.	The use of exercise imagery can positively affect autonomous motivation for physical activity.
Deci, Ryan, & Williams (1996)	Basic Psychological Needs Theory.	An individual is more likely achieve health and wellbeing if the three basic needs of competence, relatedness to others and autonomy are met.
Kirkland et al. (2011)	Social support & relatedness to others.	Where social factors support an exerciser’s feelings of autonomy, competency and relatedness there will be a positive influence on motivation.
Reis, Sheldon, Gable, Roscoe, & Ryan (2000)	Social activity types in PA.	The best predictors were meaningful talk and feeling understood and appreciated by interaction partners.

Self-Determination Theory (SDT)

Kaufman, Man & Jennett (2008) define the self-determination theory as one of human personality and motivation predicated on the assumption that people have an innate tendency toward personal growth and development facilitated when their psychological need to feel competent, autonomous, and socially related are supported. This theory is widely employed in the study of motivation in physical activity.

SDT helps answer the question of why we act over and above instinct. What makes us initiate any meaningful activity, thought, or action? It is widely held that we need to be motivated in order to act. Deci (2012) maintains that motivation in fact provides the energy for action. He believes it is not to be regarded as simply a unitary concept, a question of less or more, but rather a qualitative concept that has at its core two distinct types of motivation—controlled and autonomous. Deci (2012) refers to controlled motivation as a form of carrot and stick approach to enacting a behaviour. Guided by controlled motivation, people are prodded into action by threat and/or promise. They move themselves to act through the promise of reward and recognition or the threat of punishment, unpopularity, or deprivation (e.g., sensory, emotional, financial), (Kirkland, Karlin, Stellino, & Pulos, 2011). The action path for an individual using controlled motivation is invariably the shortest and most direct means to the desired outcome. Their internal state in this instance, according to Deci (2012) at least, is one of tension and anxiety and that the consequences of actions driven by controlled motivation are more likely to have negative consequences.

With autonomous motivation, an individual who performs an activity or task, because he or she is interested in it and enjoys doing it, is deemed driven by *self-determination*. Individuals may be driven to act from a deeply held set of core beliefs or values, their behaviours aligning with these values. Applying these types of motivation to the activity at hand may result in positive or negative outcomes for the participant. The applications of intrinsic motives, those stemming from personal choice, are more likely to result in positive consequences. Conversely, if the participant has been coerced by external social factors, there is a greater likelihood that continuation of the activity is less likely (Vallerand & Losier, 1999). The motivation to act over and above instinct according to SDT requires the satisfaction of certain conditions. The central tenet of the theory is that all individuals have an inherent predilection for personal growth and energy that is either helped or hindered by their immediate environment. The optimal conditions in this environment will allow for the satisfaction of three basic psychological needs that ensure the individual feels they have the necessary ability to act, freedom to make choices, and a sense of connection to others (Deci, 1985).

SDT is often used to guide health and well-being interventions, (Brötz, 2013). It provides a framework for addressing questions of participant motivation, intervention adherence, motivation and effective coaching and support. Deci, Ryan, & Williams (1996) maintained that people have a natural tendency toward maintaining their wellbeing, but this intent can be thwarted by conditions that abnegate the satisfaction of three basic psychological needs. The first of these, *autonomy*, is defined as an individual being totally assured they have choices and are responsible for their behaviour. The second, *competence*, is referred to as the feeling that you can actually achieve the goals you set yourself and carry out the necessary behaviours in doing so and effect outcomes. The third and final need is known as the *relatedness of others*; this necessitates that the individual be without doubt that they are understood, cared for, and valued by others close to them. The provision of both social and environmental conditions that catalyse the satisfaction of these basic needs will help promote the internalisation of positive exercise behaviours so that they are engaged in autonomously and are more likely to be maintained in the long term (Ryan, Frederick-Recascino, Lepes, Rubio, & Sheldon, 1997).

Physical activity (PA) interventions have lent themselves to application of the SDT framework. Researchers have discovered that an exerciser's goals (task improvement, pleasure, and social comparison) are triggered by a bid to satisfy the three major psychological needs: the need for autonomy; the need for competence, and the need for relatedness (Silva et al., 2010). The exerciser will be intrinsically motivated to actively seek out opportunities to satisfy these basic needs. Kirkland et al., (2011) found that in cases where social factors support an exerciser's feelings of autonomy, competency, and relatedness, there will be a positive influence on motivation; if social factors oppose satisfaction of the basic needs, there will be a negative impact on motivation. If any or all of these basic needs are not fully met, the likelihood is high that the individual will not enjoy optimal wellness and function. Chua & Koestner (2008) predicted and found that when individuals spend time alone autonomously, they counter-intuitively report lower levels of loneliness and higher levels of well-being, indicating those that are autonomously motivated may operate effectively and happily even during times of social isolation. This study however, does not cover the effects of long-term isolation on the same measures. The work may have implications for train-alone exercisers and their adherence to interventions but the phenomenon requires more investigation. Does this knowledge have relevance to the efficacy of digital exercise tracking systems for the management of athletes and rehabilitating individuals in rural and remote areas? In selecting potential users of such technology for cost-effective management of prescriptive exercise then assessment of the motivational state and needs satisfaction of the individual may help determine the suitability of the technology fit. Those that are not autonomously motivated may not be suitable candidates for self-management and monitoring using activity-tracking technology.

The SDT assertion that some behavioural regulations are imposed and others are autonomous and self-endorsed (Ryan et al., 1997), is framed by what its theorists call a continuum of autonomy. This classifies motivations under SDT, with extrinsic motivations and external regulations representing the non-autonomous or controlled end through to introjected regulation whereby the individual engages in behaviours to feel better about self-worth or to avoid harm to self-esteem. At the most autonomous end of the continuum is *identified regulation* where the individual personally values the behaviour. An evaluative framework, the *internalisation continuum*, is used to categorise distinct forms of instrumentality—external regulation, introjection, identification, and integration. Essentially, the more internalized an individual's extrinsic motivation the more autonomous they will behave in enacting target behaviour. The autonomy continuum is a construct of one of *five mini theories* that comprise the overarching SDT (Ryan et al., 1997); each of the mini theories looks at a particular facet of motivation or the functional perspective of individual personality.

(1) Cognitive Evaluation Theory (CET): The first mini theory addresses the issue of intrinsic motivation and, in particular, the influence of social factors. The impact of rewards, controls, ego-involvement, and peer pressure on intrinsic motivation is examined and evaluated.

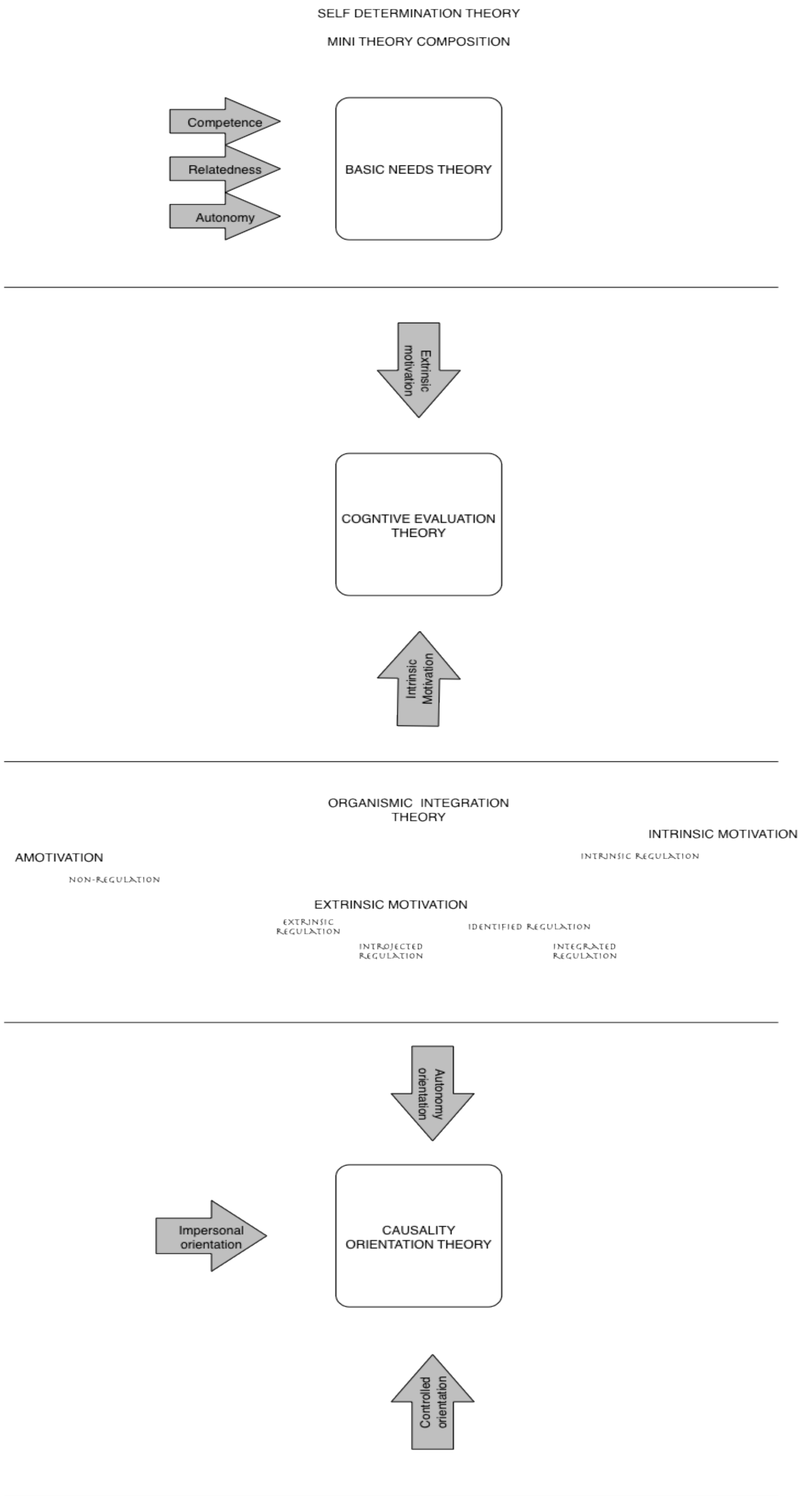
(2) Organismic Integration Theory (OIT) An organismic perspective regards people as the authors of their own behaviour, where behaviour is defined as self-governed and goal-oriented action. These actions are motivated by the satisfaction of a range of physical and psychological needs that are focused on the satisfaction of self-managed goals that align with these needs. These actions catalyse the self-management of behaviour requiring, in turn, a concentration on the boundary between the self, the environment, and the greater context. Such a focus requires close consideration of extrinsic motivations with their attributes, determinants, and effects examined, (Nota, Soresi, Ferrari, & Wehmeyer, 2011). OIT also concerns itself with the social influences that augment or retard internalisation. This mini theory closely examines those factors that pull people toward resistance, or adoption in part or full of internalisation of goals, values, and beliefs.

(3) Causality Orientations Theory (COT). This is a causality perspective examining the different ways in which people interact with their environments and adjust their behaviours. COT identifies and evaluates three types of causality orientations: *autonomous*, where the individual is interested in and values the task and what surrounds it; *control orientation*, where the individual is focused squarely on rewards, gains, and approvals; and *amotivated orientation* where the individual struggles to engage due to high levels of anxiety about competency.

(4) Basic Psychological Needs Theory (BPNT) This theory expands the examination of psychological needs, their fulfilment, the role of influencing factors, and the resultant impact on health and wellbeing. The theory contends that individuals must have all three basic psychological needs met in full at all times to avert dysfunction.

(5) Goal Contents Theory (GCT) GCT contends there is a clear difference in the ability of goal types to bring an individual health and wellbeing. Those goals of an intrinsic nature that individuals pursue—such as deepening and extending personal relationships, supporting community initiatives, and evolving their sense of self—are more likely to encourage satisfaction of autonomy, competence and relatedness needs, (Vansteenkiste, Matos, Lens, & Soenens, 2007). By contrast, personal goals based on fulfilment of extrinsic rewards, pressure, status, and promotion or aversion of punishment and mitigation of coercion are less likely to lead to basic needs satisfaction and are harder to persist with.

SDT theorists maintain intrinsic goals are positively related to wellbeing despite the motivation in pursuing the goal being of a controlled nature (Sebire, Standage, & Vansteenkiste, 2009). The five mini theories are illustrated below.



Overview Figure 3. Conceptual Model of the Self Determination Theory – Its 5 Mini Theories. Copyright©, D.L.Foy (2014).

SDT and Exercise Behaviour

SDT has been used extensively for exercise motivation and adherence. Edmunds, Ntoumanis, & Duda (2006) examined the relationship between autonomy support, psychological need satisfaction, motivational regulations, and exercise behaviour. They found that fulfilment of the three basic psychological needs (i.e., competence, autonomy, and relatedness) related to more self-determined motivational regulations. Identified and introjected regulations were shown to be positive predictors of strenuous and total exercise efforts. Competence need satisfaction also predicted, directly and indirectly through identified regulation, the occurrence of strenuous exercise effort~~.~~

People need a sense of free will and choice when setting exercise goals, (Annesi, 2002; Smith, Hauenstein, & Buchanan, 1996; Weinberg, 1994). They need to understand what information they require and what behaviours to engage in to reach these goals. Feeling they can perform the necessary actions effectively and feeling respected and cared for by advisors, coaches, and others will also assist the individual in pursuing exercise goals and adhering to programs of intervention and direction. Means of supporting this autonomous action was examined with one hundred and nine students in relation to their physical activity behaviour, (Halvari, Ulstad, Bagien, & Skjesol, 2009). It was found that autonomy support was positively linked with perceived competence, autonomous motivation, and action orientation. In turn, perceived competence (through *harmonious passion*), autonomous motivation, and action orientation were all positively associated with involvement in physical activity, whereas perceived competence and autonomous motivation were positively correlated with competitive performance~~.~~ *Harmonious passion* occurs when an individual autonomously internalises behavioural regulations around an activity that engenders a desire to engage in this activity, which in turn fosters a feeling of volition and endorsement from the individual in engaging with it, (Mageau et al., 2009).

For athletes involved in recreational and competitive sport, the coach's autonomy support facilitates self-determined motivation and sport performance, (Adie, Duda, & Ntoumanis, 2008; Adie, Duda, & Ntoumanis, 2010; Gillet, Vallerand, Amoura, & Baldes, 2010). Autonomy support predicts basic needs satisfaction that results in greater subjective vitality when engaged in sport (Adie et al., 2008). Chatzisarantis & Hagger (2009) conducted a study based on self-determination theory whilst developing and evaluating the utility of a school-based intervention to change pupils' physical activity intentions and self-reported leisure-time physical activity behaviour. Results indicated that pupils who were taught by autonomy-supportive teachers reported stronger intentions to exercise during leisure time and participated more frequently in leisure-time physical activities than pupils in the control condition.

In designing any programmatic intervention using the SDT framework, along with ensuring an autonomy-supportive environment, any practitioner or researcher must see the tripartite basic psychological needs are understood and accommodated in a practical and measurable manner. This focus on needs satisfaction should be consistent across delivery mechanisms whether they are face-to-face or digital and virtual, yet there is no evidence to date that this implantation holds true in online, mobile and digital exercise tracking systems-based interventions. Providing positive feedback to participants strengthens their confidence and motivation as well as improves competence. Markland (1999) measured self-determination, perceived competence and intrinsic motivation for exercise in 146 adult female aerobics participants. He found that variations in perceived competence positively influenced intrinsic motivation under conditions of low self-determination. This suggests that it is vital to encourage perceptions of competence among individuals low in self-determination. Removing any external rewards, punishments, or controls as well as providing a supportive, non-judgmental and positive social environment will help ensure autonomy support for the participants is important. As a sense of connection and belonging is vital to wellness, participants will benefit from being connected to others who care for them; throughout any intervention; Bailey & McLaren (2005) Reis, Sheldon, Gable, Roscoe, & Ryan (2000) examined the social activities that contribute to satisfaction of relatedness needs. The best predictors were meaningful talk and feeling understood and appreciated by interaction partners.

These findings are consistent with work being carried out in the field of weight loss and health. Silva et al., (2008) suggested that interventions grounded in SDT can be successfully implemented in the context of weight management, enhancing the internalization of more autonomous forms of behavioural regulation, and facilitating exercise adherence, while producing clinically-significant weight reduction.

Webber, Gabriele, Tate, & Dignan (2010) examined two types of motivation, autonomous and controlled, and their relationship to adherence and weight loss in a 16-week Internet weight-loss intervention. Their study design randomized two study groups of forty members each to a standard treatment control group or a motivational treatment intervention group. All participants received a two-hour weight loss education session covering diet and exercise with the recommendations for these activities being identical. Additionally, the motivational group was instructed in goal-setting practice, guided journal-keeping processes, and encouraged to set a weight loss goal. Both groups were given access to a purpose-built website that contained weekly weight loss tips, weekly lesson postings, weekly recipes, a message board feature, and links to self-help diet, exercise, and behavioural modification resources available on the web. The site also had a link to a personal on-line self-monitoring report form which participants were asked to use to report, at least weekly, their daily caloric intake and daily exercise efforts. The website was identical for the two groups with the exception of separate message boards. The authors found that the majority of participants had a significant increase in autonomous and controlled motivation. Although motivation increased initially for most participants, the group that went on to achieve a 5% weight loss sustained their autonomous motivation between 4 and 16 weeks, while the least successful group experienced a significant decrease in autonomous and controlled motivation over time. The work failed to identify specific reasons for the decline in motivation for some participants. More work is needed across a range of weight-loss cohorts to determine the factors that influence this lapse in autonomous motivation. Are participants bored with the intervention; do they require fresh content and more or less support? What remains unclear in this study is the exact effect if any on adherence during this lapse period. However, the structure of the technology integration and self-service model provides some guide to subsequent web and mobile-based implementations looking to leverage SDT for more effective weight loss interventions.

The researchers also found that autonomous motivation at four weeks was a significant predictor of adherence to self-monitoring (maintenance of a diary to log diet and activity) and weight loss. They noted a positive correlation between weight loss at four weeks and autonomous motivation, especially when compared to participants who had higher levels of controlled motivation. According to Webber et al:

> *It appears that the time period between 4 and 8 weeks may be an important window for weight control programs to consider using techniques designed to enhance autonomous motivation, including giving more intense support or different types of interventions, such as activities to enhance autonomous motivation or contact from a weight-loss counsellor in the form of e-mails, phone calls, or face-to-face meetings. (p.7)*

Teixeira, Silva, Mata, Palmeira, & Markland (2012) conducted a review of the empirical literature investigating the relations between key SDT-based constructs and exercise and physical activity behavioural outcomes. This work revealed a consistently positive support for the relationship between more autonomous forms of motivation and exercise. Identified regulation tended to predict initial/short-term adoption more emphatically than intrinsic motivation, which was shown to be more predictive of long-term exercise adherence. The literature reveals that competence satisfaction and more intrinsic motives positively predicted exercise participation across a range of samples and settings, (Teixeira, Carraça, Markland, Silva, & Ryan, 2012). Wilson et al., (2003) examined the relationships between psychological need satisfaction (competence, autonomy, and relatedness), exercise regulations, and motivational consequences promulgated by SDT, exploring changes in these constructs over the course of a 12-week prescribed exercise program. They found that competence and autonomy were positively correlated with more self-determined exercise regulations. These were more positively related to exercise behaviour, attitudes, and physical fitness. The study concluded that SDT was a viable theoretical framework to use in studying motivation in sports and exercise. The review also noted the relatively fewer instances of large-scale randomized controlled studies that had a heavy quantitative focus. Michie, Abraham, Whittington, McAteer, & Gupta (2009) in a comprehensive meta-regression, assessed the effectiveness of physical activity (PA) and healthy eating interventions and found that the most efficacious of these capitalized on specific implementations of behavioural change theory elements, in particular goal setting, feedback, and self monitoring of behaviour

Providing a means for encouraging autonomous motivation is important for athletes as well as those seeking to lose weight. Adie et al., (2008) completed a study of more than 500 adult sport participants with the objective of testing the efficacy of Basic Needs Theory (one of the five SDT mini-theories), for coach autonomy support, motivational processes and the well/ill-being of adult sports participants. The results showed that coach autonomy support (the level of participant autonomous motivation afforded by the actions, behaviours, and performance environment provided by the coach) predicted participant's basic need satisfaction for autonomy, competence, and relatedness. In turn, basic need satisfaction predicted greater subjective vitality—a greater willingness to train, compete, and enjoy the activities with energy when engaged in sport.

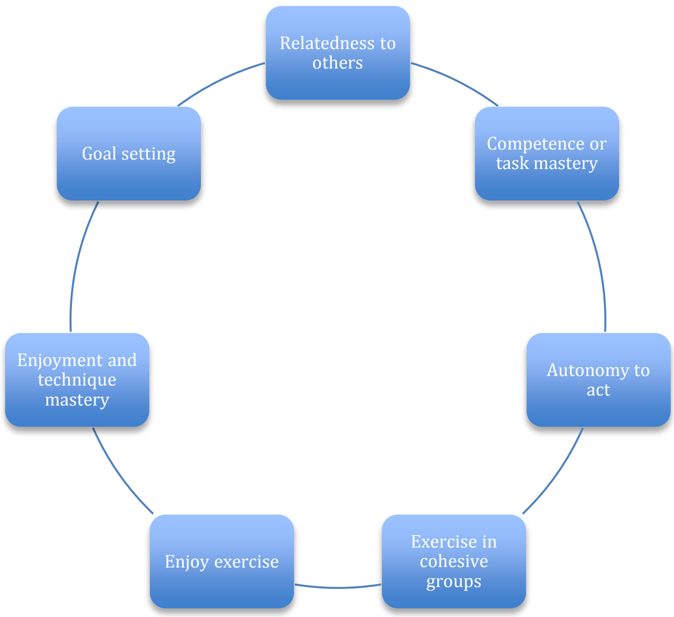
SDT-Social Support and Exercise

Of the key elements of SDT, the Cognitive Evaluation Theory (CET) mini-theory, with its focus on intrinsic motivation and the influence of social factors, has attracted less specific attention from researchers. Yet, the salience of peer influence and group-based dynamics on exercise and physical activity cannot be denied. Social support is seen as a recurrent predictor of exercise adherence in most studies of intervention effectiveness (Sherwood & Jeffery, 2000). Oka et al., (1995) examined the types of social support that best predict adherence at different time points during a one-year endurance exercise program in 269 women and men ages 50 to 65 years. Results indicate that social support specific to exercise was a better predictor of exercise adherence than general social support. For digital exercise tracking systems, this may be related to an individual's tendency to join online social network groups that are homophilous to that individual's interests and social identification, including physical activity, (Rovniak et al., 2013). Social psychologists recognise social support may work in two main ways: first, in what is known as a main effects model, social support exercises bestow positive effects on emotional well-being, anxiety, and physiological health; and secondly, the stress buffering model that acts to mitigate the effects of stress. Rees & Hardy (2004) investigated the matching of social support dimensions with stressors as part of examining the main and stress-buffering effects of social support upon factors underlying performance in tennis. They found that players experiencing competition pressure were helped by the perception they had someone to listen to them and provide moral support. Similarly, social support mechanisms were a direct aid to sustaining positive self-esteem under competitive pressure. Having access to a friendly and positive listener able to provide affirmative statements that maintained the player's self-belief was a stress buffering aid. In a subsequent study, (Rees & Freeman, 2009) examined the relationship between social support and objective task performance in a field setting with a sample size of 197 young adult male golfers, with a mean age of 23.13 years. Their moderated mediation analysis demonstrated that *social support was associated with increases in self-efficacy, and in turn, self-efficacy was associated with enhanced performance*, but that this effect was only salient at moderate to high levels of stressors. Its narrow participant base; male and high performance athletes only limit the study.

The positive affects of social support mechanisms are not restricted to competitive sport; (Fraser & Spink, 2002) found that *cohesion and social support variables both contributed to the successful prediction of attendance at exercise* *programs* in a group of women completing prescriptive exercise for health-related outcomes.

Stephens and Craig (1990, as cited in Annesi, 1999, p 544) concluded most adult participants would prefer to exercise with others rather than alone; Massie and Shephard (1971, cited in Annesi, 1999, p 544) found group-based program attendance exceeds individually based programs. Burke, Carron, & Eys (2006) ran a study with university-age students to determine their most and least preferred physical activity context from the choices given of exercising (a) in a structured exercise class, (b) with others outside of a structured exercise class, (c) alone in an exercise setting, and (d) completely alone. The setting selected as the most preferred was (b) *exercising with others outside of a structured exercise class*; the **least preferred setting** was (d) *exercising completely alone*. Although limited by the cohort age group (college students only), the basic premise of the study was ratified in a subsequent meta-analysis by (Carron, 2010) that compared the relative merits of different contexts typically employed in the physical activity intervention literature for five categories of outcomes: adherence, social interaction, quality of life, physiological effectiveness, and functional effectiveness. It was found that the common trend across dependent variables was exercising in a true group was superior to exercising in a standard exercise class, which in turn, did not differ from exercising at home with contact. This latter distinction may have relevance to those users exercising on their own but uploading their exercise sessions to online exercise social networks such as *Endomondo® and I Map My Fitness®* and may warrant a revisit of the original study design such that it can accommodate digital exercise tracking systems investigations. Furthermore, exercising at home with contact was superior to exercising at home without contact. There are implications for practitioners from this work by way of ascertaining the balance between contact and social support in physical activity interventions.

A visual summary of the main points concluded from the review of available evidence for the Self Determination Theory identifies those factors that influence exercise adherence in Figure 2.



Overview Figure 4. SDT main elements affecting exercise adherence. Copyright©, D.L.Foy (2014).

Along with SDT, the Social Cognitive Model (SCM) and the Transtheoretical Model (DiClemente, 2007) are well-established health behaviour change models used extensively in public health policy and lifestyle interventions that address chronic health conditions. The established literature for the SCM is evaluated to identify potential insights into its role in physical activity interventions as parts of it are used in health behaviour apps; (White et al., 2016).

If we are to determine the relevance of theories such as SDT and SCM to improving the design of activity tracking systems intended to assist individuals persist with exercise then a proper appraisal of their evidence is warranted.

Social Cognitive Model (SCM)

The social cognitive model (SCM) posits individuals adopt new behaviours and acquire additional knowledge by observing others. Understanding behaviour changes requires a balanced understanding and assessment of people, their environment, and behaviour. Environment refers to the social and physical surrounds affecting an individual. It is the environment in concert with the situation (a person's cognitive model of the environment) that affects a person's behaviour. There is a constant dynamic between people, environment, and behaviour that have each element directly influencing another. Depending on whether people are rewarded or punished for their behaviour and the outcome of the behaviour, determines whether or not that behaviour may be modelled. Bandura (1997) posits that for an individual to enact behaviour, they need to understand the behaviour and be confident they can perform it. The more confident a person is about their ability to enact a behaviour, the more likely it is they will; this is referred to as a person's **self-efficacy**. This finding has shown to be applicable to mastery of information technologies (IT) (Bates & Khasawneh, 2007; Chau, 2001). Malliari, Korobili, & Togia (2012), in a comprehensive investigation of university student IT competencies and self-efficacy, found the frequency of IT use was a strong predictor of IT self-efficacy, and both frequency of use and experience were predictors of computer competence

Evidence that explains the role of technology self-efficacy and its association with the effective use of digital exercise trackers is scant at this early stage of investigation. Kim (2014) in a small-scale (forty four female college students) study of physical activity trackers over a ninety-day data-logging period found that the ease of use of a particular device stands as the most significant barrier to increasing the efficacy of self-tracking. More work is warranted in determining exactly how the design of digital exercise trackers and their software can be improved to elevate user technology self-efficacy, as it would seem unlikely that low technology self-efficacy in terms of device use could lead to optimum physical activity self-efficacy using the technology. Andrew, Borriello, & Fogarty (2011) in an examination of the role of self-efficacy on personal informatics system design, identified system usability, system alignment with user goals, and the failure points of the technology as three key design factors that directly affect the self-efficacy of individuals using personal informatics systems.

Self-Efficacy Explored

Bandura (2004) proposed four different types of self-efficacy. **Mastery** is an individual's task competency set; the better performed and more able a person is to complete a task, the higher their self-efficacy and the greater the chance they will commence and complete a task satisfactorily. **Social modelling** is the study of the imitation of another's behaviour in order to acquire it. **Social persuasion**, on the other hand, looks at the communication web of support and influence exerted on an individual to encourage and motivate them to act. **Self-efficacy** also accounts for an individual's ability to respond emotionally to their environment; self-efficacy improves if an individual reacts positively to these external factors. Finally, self-efficacy is strongly influenced by an individual's self-regulatory ability that reflects the consistency and accuracy of their self-observation skills. It is to self-efficacy that most health researchers have turned when looking to understand and explain the challenge of adherence to exercise intervention and the treatment of chronic health conditions. Bandura (2004) originally posited, “Self-efficacy beliefs operate together with goals, outcome expectations, and perceived environmental impediments and facilitators in the regulation of human motivation, behaviour, and well-being” (p.143).

Expectation of Outcomes

If an individual lacks the knowledge and understanding of their health condition and the positive effects that change to their health and lifestyle choices may have, they are unlikely to change their existing beliefs or behaviours. This relates to their state of personal efficacy; if a person believes that despite making a concerted effort they cannot produce the change they desire, it is unlikely they will persist with these efforts when facing hurdles. They must be able to understand their health, the desired behaviour, and the implications for their health and wellbeing if they embrace the behaviour. An expectation of outcomes affects health behaviour; people weigh up the prospective enjoyment and benefits from being active with the possible levels of discomfort and potential material gains and losses. If the pain and losses (of personal time, of failure to complete an exercise mode correctly or fully) outweigh the potential health gains, many will opt out of the activity. Along with evaluating physical outcomes, a person will assess the impact on social support or sanctions that participating in a behaviour will bring. These physical and social outcomes are balanced in conjunction with the individual’s evaluation of how their health behaviour and status impact their self-esteem and self-worth. If behaviour aligns with positive self-interest, an individual is more likely to implement it.

Bandura goes further; along with knowledge, personal efficacy, and expectation of outcomes, he believes that *proximal goal setting and management from an individual will aid motivation and direct behavioural change*. The nature and extent of a person’s goal will in turn be driven by the strength and resilience of self-efficacy. Those with a strong self-efficacy will set more aspirational goals and persist toward their realisation despite the setbacks and disappointment they experience in pursuit. The strongly efficacious will have far greater confidence that their efforts will produce positive outcomes than those with lesser levels of self-efficacy.

The central tenets of SCM have been subjected to rigorous examination by health researchers and practitioners looking for a robust theoretical framework to guide interventions and measure their efficacy. Anderson, Winett, & Wojcik (2011a) in a study of an adult population and its physical activity behaviour as part of an examination of health promotion, discovered that self-regulation had the strongest effect on physical activity levels. Social support in turn affected physical activity as a precursor to both self-efficacy and self-regulation. Rovniak, Anderson, Winett, & Stephens (2002) examined the social cognitive determinants of physical activity among university students and determined that social support influenced physical activity through its effect on self-efficacy and self-efficacy in turn through its effect on self-regulation (goals and plans). In both studies, the outcome expectations of participants had a negligible effect on their physical activity behaviours. Plotnikoff, Lippke, Courneya, Birkett, & Sigal (2008) completed a study of physical activity among a group of type 1 and type 2 diabetes patients and found that self-efficacy and self-regulation (instantiated as activity-specific goals) were direct predictors of physical activity. Further, outcome expectations, self-efficacy, and social support predicted self-regulation which, successively, predicted physical activity. In applying the basic constructs of the SCM to determine the predictors of physical activity among people living with spinal cord injury, (Ginis et al., 2011) discovered that self-regulation was the sole, significant, and direct predictor.

Self-regulation

Doerksen, Umstattd, & McAule (2009) found *that among college freshmen, self-efficacy and self-regulation (goal setting and management) were strong predictors of vigorous physical activity* but were insignificant in predicting moderate physical activity levels. There have been contradictory findings across population groups as well as some consistent findings; self-efficacy and self-regulation and social support are strongly implicated as predictors of physical activity. However, outcome expectations are not consistently evident as a strong predictor of physical activity and there has been insufficient attention paid as to why this appears to be the case.

A visual summary of the main points concluded from the review of available evidence for the Social Cognitive Model in Figure 3, identifies those factors that influence exercise behaviour.

Overview Figure 5. SCM factors affecting exercise behaviour. Copyright© D.L.Foy (2014)

Mobile and Internet technologies are being used more widely to provide convenient means of setting and managing goals for exercise as part of efforts to encourage positive health behaviour change using technology and making use of established theoretical frameworks, (Klasnja, Consolvo, & Pratt, 2011; McMahon, Vankipuram, Hekler, & Fleury, 2014; ; O'Reilly & Spruijt-Metz, 2013.

These long-established, validated and applied behaviour change theories were devised well before the advent of wearable self-monitoring systems used now to assist physical activity tracking. However they form a bedrock for understanding exactly what is needed to motivate and support individuals engaged in physical activity so that they may persist in this healthy behaviour. Since these theories were first implemented, the advent of wearables has proceeded with their creators holding similar objectives to the original theorists but, driven by largely commercial interests, may have missed opportunities to better leverage existing evidence. Certainly, the most recent research into wearables use indicates an alarmingly high abandonment rate by their users with something like one in three US consumer abandoning their use of activity tracking wearable withint three months of purchase, (Endeavour Partners, 2014).

Given this, researchers have been frantically trying to bridge the gap between established health behaviour change theories. The goal being to create technologies using evidence-based means for improving the design of the systems and reducing abandonment. The following review of the literature delves into emerging models aimed to improve the theoretical framework used to design activity tracking and similar behaviour change and support systems.

Persuasive System Design Models

The following table summarises the main studies, their investigative topics and resultant findings for this research area.

Table 2 *Summary of Literature Review for Persuasive Systems Design.*

Study	Topic	Finding
(Stibe & Oinas-Kukkonen, 2014b)	Role of PSD design principles in a public display system on user feedback.	The seven social influence design principles of BCSS explained more than half (52%) of the variance in the perceived persuasiveness of the system.
(Kelders et. al. 2012)	PSD influence on web-based health interventions.	About 50% of participants across the studies adhered to the web-based intervention over the period of the intervention. More extensive use of dialogue support significantly predicted better adherence.
(Stibe and Oinas-Kukkonen, 2012)	PSD elements present in Twitter that influence user behaviours and attitudes.	Social learning and facilitation are PSD techniques in Twitter that affect user content generation and tweeting behaviour. Systems trustworthiness and credibility may affect Twitter usage.
(Lehto & Oinas-Kukkonen, 2011)	Meta-review of literature investigated PSD application in web-based substance use interventions.	Reduction, self-monitoring, personalization and simulation were the most widely used features for primary task support. Tailoring was rarely used although social support features were in widespread use.

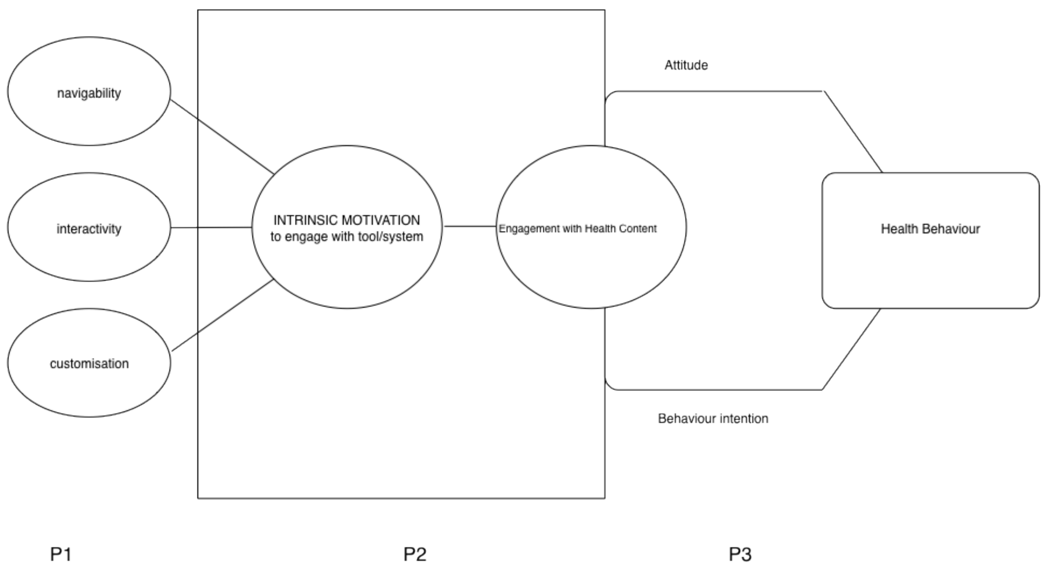
Fogg, Bedichevsky, & Tester (1998) defined **persuasive technology** as:

"*Simply put, a persuasive computer is an interactive technology that changes a person's attitudes or behaviours. Persuasion is an attempt to shape, reinforce, or change behaviours, feelings, or thoughts about an issue, object, or action*" (p. 71).

The emergence of ambient persuasive technology and its impact on human social interactions has triggered a flurry of recent research into how such technology can be designed to change human behaviour and attitudes. A key area of research focus is health care. Kraft, Drozd, & Olsen, 2009; Krebs, Prochaska, & Rossi (2010) indicated computer-based interventions have been shown to be effective across a range of target health behaviours including weight loss, physical activity, and smoking cessation. Although more established theoretical frameworks including SCM and SDT have been addressed in detail, the motivational and environmental (physical, social, and psychological) factors affecting health behaviour have not been examined for their role in terms of a persuasive technology content, structure, function, and intent. To fill this gap, emerging theories have recently been proposed to encourage evidence-based research into how to best make use of persuasive technology such as exercise and medical sensor devices, mobile phone-based software applications, and online social networks. Foremost among these new theories are Fogg's Behavioural Model (Fogg, Bedichevsky, & Tester, 1998), the Behaviour Change Support System (BCSS) Model (Oinas-Kukkonen, 2013), and the Motivational Technologies Theory (Sundar et al., 2012).

Sundar's Motivational Technologies Theory

Sundar et al., (2012) proposed that designers of and stakeholders in health behaviour intervention technologies focus greater effort on improving the structural elements of these systems that elicit the greater sustained intrinsic motivation of users. These structural elements should operationalise those fundamental attributes of SDT that have been shown to be necessary in improving intrinsic motivation in particular—autonomy, relatedness to others, and competence. This alignment between SDT attributes and functional design factors in the design of what the authors refer to as *motivational technologies* is shown in Figure 5.



Overview Figure 6. A Theoretical model of motivational technology to promote preventive health behaviours.

From "Motivational Technologies: A Theoretical Framework for Designing Preventive Health Applications" by S.Sundar, S.Bellur & H.Jia, 2012, Persuasive Technology. Design for Health & Safety Lecture Notes in Computer Science 7284, p.116. Reprinted with permission.

The model illustrates the role the SDT corollaries instantiated by the systems design elements of navigability, interactivity, and customizability play in influencing the intrinsic motivation of users who engage with preventive health systems which in turn influence health behaviour, attitude, and intent. The model contains three key propositions:

P1: Optimal levels of navigability, interactivity, and customisation will lead to higher levels of intrinsic motivation through their corollaries in SDT—competence, relatedness, and autonomy.

P2: Higher levels of intrinsic motivation will lead to greater engagement with health content.

P3: Higher levels of engagement with health content will lead to better attitudes and adoption of continuous health behaviours.

This model is predicated on a mapping from the SDT-sourced three basic psychological needs. It aligns the satisfaction for optimal wellbeing with systems design constructs; competence, autonomy, and relatedness to others are mapped to the core systems design elements of navigability, customizability, and interactivity respectively. Navigability is simply an effective design of traversal mechanisms in systems such that users are more easily and consistently able to use the system to realize systems use goal without losing their context of use and purpose. The model uses evidence spanning Information Foraging Theory, (Olston, 2003; Pirolli, 1999) as well as User Control Theory (Eveland & Dunwoody, 2001) to emphasise the role of increased levels of user competence in smart and effective navigation design in systems, with (Sundar, 2007) supporting the salience of this to emotional and behavioural outcomes. It points to a belief that a user's *ability to absorb content and be open to persuasion is affected by their experiences in navigating highly effective interfaces such that they experience high levels of competence or self-efficacy*.

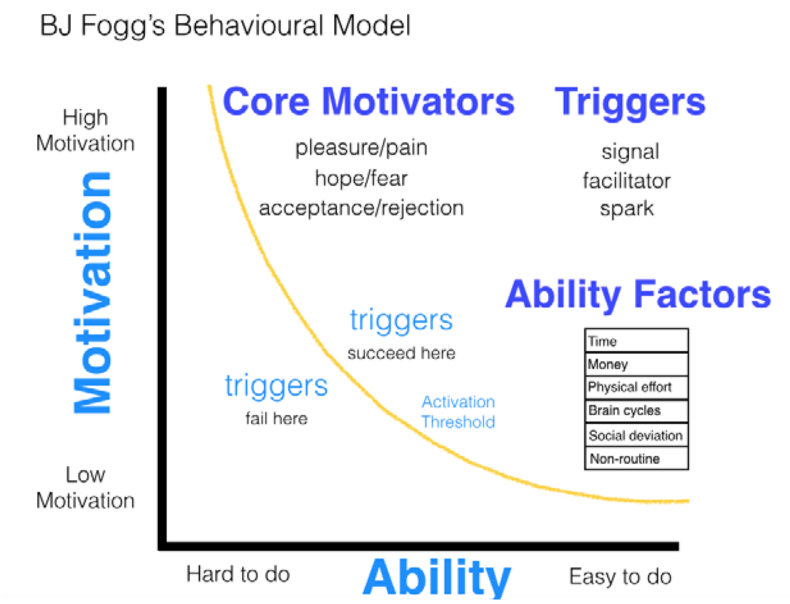
The second SDT systems design corollary is the mapping of relatedness to others to systems interactivity. Bandura (2004) points to the power of socially mediated pathways in influencing health promotion for behavioural change, a power greatly amplified by the proliferation of online social networks, (Househ, Borycki, & Kushniruk, 2014; Korda & Itani, 2013). The model insists that the incorporation of systems *functions that encourage interactivity with other users of common interest will improve the potential for increased relatedness of users*. It offers no empirical proof of this.

The third and final SDT systems design corollary used by the model is that of customisation mapped to autonomy. In persuasive technology parlance, customisation is often equated to tunnelling, a design functionality that has been identified as having a positive effect on health behaviour as implemented through technology-based interventions (Krebs et al., 2010; Noar, Benac, & Harris, 2007). Customisation brings with it a powerful sense of agency to users, permitting broad ranging preferences and settings in systems that support it (Sundar & Marathe, 2010). It thereby increases autonomy and self-determination, with the evidence from education indicating that choice can motivate the learner. In a meta-analysis of choice on intrinsic motivation and related outcomes, (Patall, Cooper, & Robinson, 2008) found that providing choice enhanced intrinsic motivation, effort, task performance, and perceived competence, among other outcomes.

Sundar, Bellur, and Jia (2012) believe the model has merit as a means to move beyond persuasive technologies to providing the ability to "*increase human ability, provide experiences and create relationships in order to persuade as well as motivate*" (p.118). There is, however, scant empirical evidence that this is the case with available technologies in the preventive health domain. The alignment of systems functionality with SDT core elements may be sound given the thrust of the model is to aid in optimizing autonomy and sustainable intrinsic motivation but this likely requires a broader and deeper base of quantitative and qualitative evidence and at the very least formulation of standardised and validated scales that can identify the presence and dimensions of model factors in preventive technology tools. Startign with usingvalidated scales on large user populations to determine the presence of the SDT satisfied needs elements in a system and their satisfaction or otherwise by the system for a representative sample of users. This gap has provided impetus to the study direction of this thesis.

Fogg Behavioural Model

The fundamental premise of this model is that *for a desired behaviour to be enacted, there must be a confluence of three elements: motivation, ability and a trigger*. If behaviour fails to occur, it is because one or more of these factors is missing. The structure of the theory rests on three elements that in turn comprise subcomponents as follows: motivation has three core types, ability comprises six factors and there are three main forms of trigger. A visual overview of FBM illustrates the basic concepts in Figure 6.



Overview Figure 7. Fogg's Behavioural Model

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FBM implies that motivation and ability are in effect traded-off such that those with low motivation can still complete an activity that is simple; inversely, if motivation is extreme, those with low ability may still perform the activity. Fogg believes *most people possess a modest level of both motivation and ability, both of which can be manipulated by persuasive technology*, with the example most commonly given in his literature being of the Amazon.com function "1-click-to-purchase"; a function simple enough to provide almost anybody with the ability to purchase online. On the matter of triggers, FBM maintains that *without an appropriate trigger, target behaviour will not be enacted.* Triggers have a variety of forms—physical, sensory, electronic, and social for example. Irrespective of the form of the trigger they all exhibit three essential characteristics: Firstly, the trigger must be detectable, secondly, the trigger must have an association with the target behaviour and finally, the trigger will only occur if the individual concerned possesses the threshold level of motivation and ability.

FBM elements of motivation

The aim, according to FBM, is for persuasive technology designers to *shift individuals above the behaviour activation threshold* such that those with high ability and low motivation experience the raised levels of motivation required. FBM details three main motivators, each with two aspects. Pleasure and pain are regarded as immediate motivators and may occur without anticipation. The literature provides very little beyond this by way of explanation. Pleasure and pain according to SDT can act as powerful extrinsic motivators that can yield effective immediate behaviours but not sustained long-term behavioural change. The motivators, hope and fear have some corollary with outcomes expectations as detailed in the SCM in that both are based on anticipation or expectation when using an information system. As an example, individuals join online or mobile dating services in the hope of meeting a suitable partner, whereas those that download a "find my phone" app do so out of fear of the phone being lost or stolen. Fogg makes the point that the motivation of the individual to be accepted by their social group has risen to the fore online through the proliferation of web and mobile-based social networks. Uploading multimedia content, commenting, tweeting, and liking in such a way as to garner social acceptance, are all-powerful motivators in the use of contemporary persuasive technology.

FBM elements of ability

Fogg emphasizes the importance of simplicity of use for persuasive technology as he asserts that the individual user is fundamentally lazy and to have them enact target behaviour, the system has to ensure the necessary level of ability to use it effectively is low. The simplicity of a system may help change behaviours. The FBM Theory details these six elements of ability: time, money, physical effort, brain cycles, social deviance, and routine. If the target behaviour requires time to learn and or enact, it is deemed not simple by FBM. Given the disastrous contribution of physical inactivity to death by non-communicable disease globally, (La Vecchia, Gallus, & Garattini, 2012) puts the number at 6-10% of all deaths, the effort required to engage in regular physical activity can be a deterrent. For designers of persuasive technology targeting positive exercise behaviour, there is a need to ensure minimal physical effort required for users to set-up, configure, use, update or share any system designed to engage them in physical activity. Any system intended to influence behaviour that necessitates physical effort to use it, is not considered as simple by the ~~t~~model. FBM maintains that to have users think deeply and often when using a persuasive technology impedes the initiation of the behaviour intended from using the system. If a system necessitates or permits that an individual indulge in a behaviour that is socially deviant and unacceptable it is not a simple matter for that individual. This may occur in online social networks that permit or fail to manage such behaviour, through poor role conflict and insufficient anonymity management. People tend to repeat behaviours they have become conditioned to, preferring activities that are not intrusive and routine. Any system targeting behavioural influence or change should be simple enough to be easily repeated until it becomes another routine activity.

FBM types of triggers

A trigger according to FBM cues target behaviour for an individual. In cases where an individual has the necessary ability and motivation, a trigger is all that is required to elicit the desired behaviour. The designer must ensure the trigger is recognised, is associated with the target behaviour, and is presented to users at a moment when they can take action. There exist three types of triggers accounted for by the FBM; *sparks, facilitators and signals*. A **spark** is a trigger incorporated in tandem with a motivational element, with the trigger acting as a catalytic agent to elevate motivation. For example, in an online exercise community, a spark trigger may include an uploaded video of a comparable individual achieving a target weight or an individual's successful participation in a goal event or a positive reinforcement text sent to the individual's mobile phone affirming their desired goal task. **Facilitators** are those triggers most often associated with individuals exhibiting high motivation but low ability, it aims to trigger the target behaviour in a way that makes it easy to accomplish with the system. For example, an exercise sensor device that automatically acquires and confirms a GPS signal and/or automatically updates the device firmware when it is connected to a computer provides a facilitator function. To ask a user to traverse a number of interface interactions such as menus with multiple choices and potential activity flow disconnects can act as a deterrent to full and complete use of the device. A **signal** trigger is something that is simply a task reminder; it is assumed the user has reached the appropriate behaviour activation threshold, they have the ability and motivation, and the signal trigger is needed to simply signify when the behaviour is appropriate at the time. For example, when an exercise session is completed using an exercise sensor device and the session data needs to be saved.

Summary of FBM

The fundamental premise of the theory is that for a desired behaviour to be enacted, there must be a confluence of three elements: motivation, ability and a trigger. If behaviour fails to occur, it is because one or more of these factors is missing. The core elements of the theory and its application are visually summarised in Figure 7.

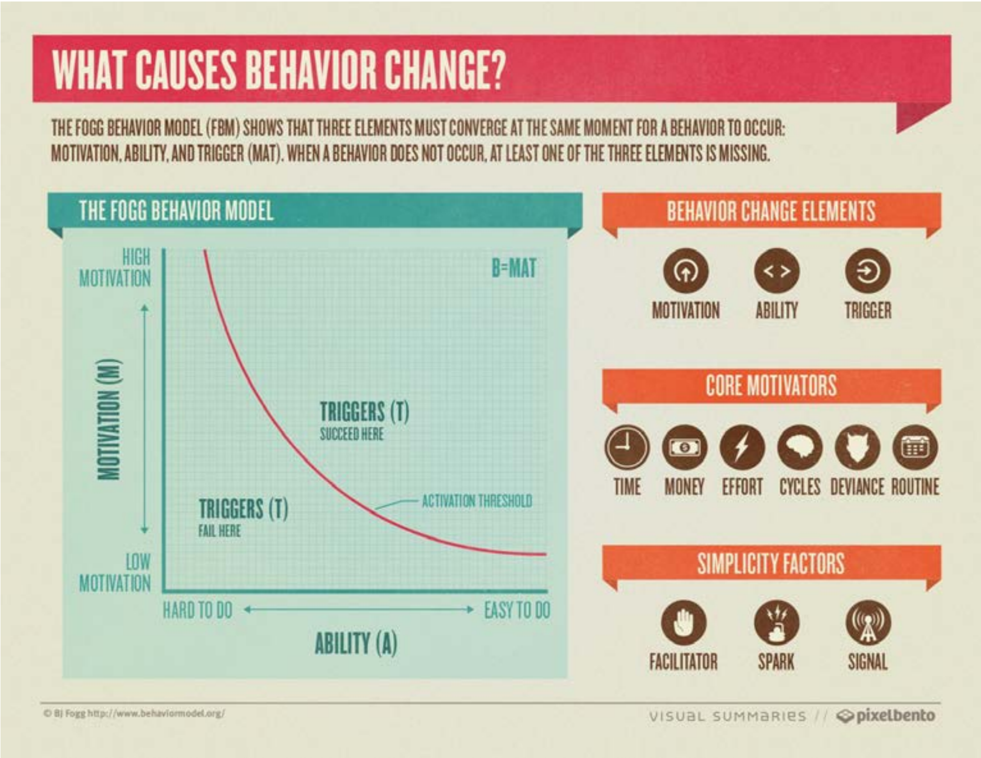

Figure 7. Summary of key elements of FBM.

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The Behavioural Change Support System (BCSS)

Oinas-Kukkonen (2013) argued that to design and assess the behavioural change of persuasive technology, it is vital the intent and persuasive potential of the system be understood along with actually measuring any behavioural change using standard scales; existing theories do not adequately explain, describe, or apply this intent and persuasiveness to technology. Oinas-Kukkonen (2010), in what is essentially a constructivist view of human behaviour, defined an alternate approach as the behaviour change support system (BCSS) defined as

> "*A socio-technical information system with psychological and behavioural outcomes designed to form, alter or reinforce attitudes, behaviours or an act of complying without using coercion or deception*" (p. 6).

BCSS contends that technology can be designed to form, alter, or reinforce attitudes, behaviours, and compliance with design and research guided by what is termed their O/C Matrix as defined in Table 2.

Table 3 *BCSS outcome/change design matrix. (Oinas-Kukkonen, 2010).*

	C-Change	B-Change	A-Change
F-Outcome	Forming an act or complying (F/C)	Forming a behaviour (F/B)	Forming an attitude (F/A)
A-Outcome	Altering an act or complying (A/C)	Altering a behaviour (A/B)	Altering an attitude (A/A)
R-Outcome	Reinforcing an act of complying (R/C)	Reinforcing a behaviour (R/B)	Reinforcing an attitude (R/C)

Forming outcomes refers to the creation of a new pattern such as use of a Bluetooth-enabled glucometer for a type-2 diabetes mellitus patient as part of a new primary health recommendation whereas an altering outcome occurs when there is a change to a standard response sought for an individual, for example increasing exercise levels for an obese patient who has impaired glucose tolerance. By contrast, a reinforcing outcome is used in BCSS to refer to attitudes or behaviours that require reinforcement, increasing their resistance to change. The change scale is set in an ascending order of difficulty in the matrix such that a change requiring compliance to an activity is regarded as easier and simpler than a change required to alter an attitude. Using a real-world example to operationalise this comparison, a text message reminder for medication adherence constitutes a simpler change for an individual with high cholesterol levels than a system designed to change the attitude of the same individual to modify exercise and diet regimes. BCSS are characterised as autogenous, enabling people to use information technology to change their attitudes or behaviour through evolving their own motivation or goal set. They also require a design-sense that optimises persistent use; for without this, changes to attitude and behaviour are less likely to occur.

Transformation from the O/C design matrix to design proper requires consideration of the *seven postulates* of Persuasive System Design (PSD): (i) technology is never neutral, it always has an influence on the user; (ii) the system must reinforce and correlate with the user views and so must be organised and consistent with these; (iii) persuasion is incremental; (iv) persuasion can follow direct and indirect routes; (v) BCSS must be useful and easy to use; (vi) persuasion via a BCSS should never overwhelm a user's primary task; and (vii) persuasion via BCSS must be transparent.

BCSS First Postulate

This regards technology as *never neutral* and that persuasion is a process and not an act with fluctuations in this process dictated largely by the user's goals and environment. A user may invest in a *fitbit®* device with the initial goal of tracking daily step activity as directed by a health practitioner but with further use, the same user may wish to determine calorie expenditure and observe the efforts of others using the device. A viable persuasive system will be one designed to adapt to changing user goals, knowledge, system efficacy, and likely environment fluctuations such as usage cessation and other alterations in the state of the user—health condition, skill, or activity proficiency. The authors maintain that *a persuasive system needs to be adaptive*.

BCSS Second Postulate

This builds on the original work of (Cialdini, Petty, & Cacioppo, 1981; Festinger, 1957; Simons & Jones, 2011). It proposes that *people like their views about the world to be organised and consistent*. Cognitive consistency is integral to motivations for attitude and behaviour change; when a cognitive inconsistency is present an individual may be motivated toward a change~~.~~

Individuals will constantly strive to create harmony and consistency between their own expectations and daily reality. Festinger proposed that people would act to achieve such consistency by adjusting the dissonant behaviour or cognition through changing it or by introducing new behaviours or cognition. Oinas-Kukkonen (2013), submits that persuasive systems designers can apply cognitive dissonance by incorporating information for access by a user that is inconsistent with their beliefs and cognition, thereby eliciting a possible trigger to change behaviour. It may be that in the case of exercise-based quantified-self technologies and social networks that the exposure of user data or scores for health indicators such as Body Mass Index (BMI) and fitness, particularly when disclosed in a social network of peers may cause some dissonance if that individual seeks a state of improved fitness and wellbeing. *Persuasive systems should provide support for users to make commitments, either public and or private*, as consistent with the work of Cialdini et al. (1981), that found people were more likely to honour their commitment of meeting their stated goals if such goals and commitments were made orally in public or put to writing. In social network systems such as Facebook, the system enables a user to state their goal or commitment to that goal using the status update facility and share that statement to all or some of their online contacts. Torning & Oinas-Kukkonen (2009) insist that if systems support the making of commitments, then they will more likely persuade users.

BCSS Third Postulate

This states that direct and indirect routes are key persuasion strategies, which means a user's personal background (problem domain knowledge and skills, ITC self-efficacy, motivation levels and type) and the use situation for the technology will influence how they process systems-related information. Consistent with FBM, PSD insists that *the higher a user's motivation and ability, the more likely it is they will be interested in the content of a persuasive system message than if they possess lower ability and motivation*. It follows that persuasive systems designers should focus on lowering ability thresholds for their systems to encourage greater accessibility and attraction to the persuasive message for low ability users. Designers could consider the use of a standardised psychosocial measurement tool that clarifies and classifies a user’s motivation and ability as part of the design and development process.

BCSS Fourth Postulate

This states that persuasion is often *incremental*. Evans (2005)) states that “people like small amounts of change but do not adapt well to large amounts of variation" (p.638).and described three design schemes to motivate positive behaviour change through the modification of architectural elements and integration of interactive interfaces into the environment of a subway station. He found it is easier to initiate people into doing a series of actions through incremental suggestions rather than a one-time consolidated suggestion, or as he suggests, "the most important aspect of incremental persuasion is that there are only suggestions, no obligations"(p. 640). Stibe, Oinas-Kukkonen, Bērzicna, & Pahnila (2011) investigated features of Twitter to uncover inbuilt persuasion patterns that may influence users’ behaviours and attitudes by using frameworks and measures of success for Behaviour Change Support Systems (BCSSs). They found that experienced users tweeted more than new users and this behaviour developed incrementally; an activity (tweet frequency) they proposed might lead to behaviour change. It was also found that experienced users generated more content than new users, a phenomenon the authors attributed to *vicarious learning*. Bandura (2001) indicated "virtually all behavioural cognitive, and affective learning from direct experience can be achieved vicariously by observing people's actions and its consequences for them" (p.271). This implies that *individuals learn not only from their own experience but also by observing the behaviours of others in an online environment.* In this case, less experienced Twitter users may observe others posting tweets and learn from that. This has a direct corollary with the PSD design principle of social learning (Oinas-Kukkonen, 2013). At the same time, social facilitation, another persuasive software feature from the same social influence category, may play a significant role in changing users' behaviour toward more active content generation. Social facilitation examines behaviour when it occurs in the presence of other people also engaged in the same activity (Guerin, 1993; Zajonc, 1965). The same principle may explain the increased frequency of tweeting that was found to be more inherent for users with a longer experience in Twitter, (Stibe et al., 2011). When someone else is present, people tend to behave in accordance with socially expected standards of performance. The second main effect is an increase in alertness or attention, which may impact on their performance in different ways: if the task is difficult or new and if their attention is diverted elsewhere the user's performance may suffer; if the task is easy, they might be more relaxed if they have time to watch what people are doing (Guerin, 1993).

The discovery that more experienced Twitter users have higher trust in information on Twitter, Stibe et al., (2011) may be associated with the PSD design principle of system trustworthiness and credibility.

BCSS Fifth, Sixth and Seventh Postulates

The fifth postulate states that persuasion through persuasive systems should always be open; the intent and motivation of the designer should be clear (Kulyk, op den Akker, Klaassen, & van Gemert-Pijnen, 2014). The sixth postulate states that *persuasive systems should be unobtrusive* (Kulyk et al., 2014; Lehto, Kukkonen, Pätiälä, & Saarelma, 2013)). According to Oinas-Kukkonen (2013), they should not intrude into the user's primary task space unwittingly and it could therefore be supposed that their design should be context-sensitive and be placed in a state of low or no access when not required or in a standby state. The seventh and final postulate serves more as a common sense reminder than a theoretical construct, which is to ensure systems are easy to use and useful else they will not be used and the level of persuasion will likely be low as a result.

Once the designer accommodates these postulates, attention needs to be drawn to an analysis of the persuasion context through consideration of the persuasion intent, event and strategy. This is done against the guidelines of the O/C design matrix. From this, the designer balances the persuasion message and conduit, the user and their context or situation model and technical issues of user interface, hardware platforms and software architecture, libraries standards, operating systems etc. BCSS does offer a range of specific software features for consideration organised under the categories of task support, computer-human dialogue support, perceived system credibility and social influences, as detailed in Figure 8.

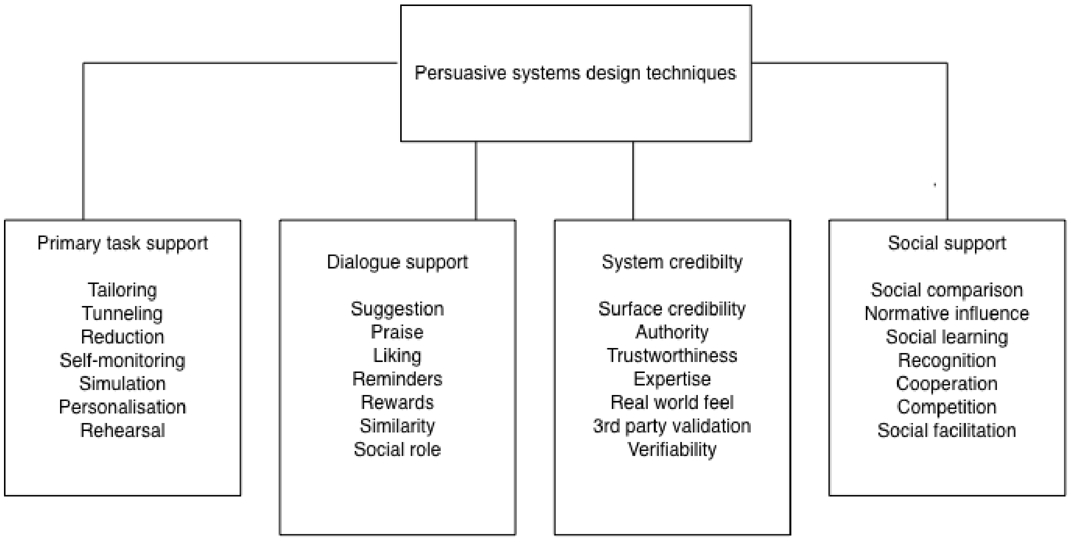


Figure 8. Persuasive system design (PSD) techniques.

Adapted from "Behaviour Change Support Systems: The Next Frontier for Web Science" by H. Oinas-Kukkonen, 2010, In Proceedings of the WebSci 2010:Extending the Frontiers of Science Online, p6. Copyright 2010 Web Science Trust. Reprinted with permission.

Of these, BCSS researchers frequently identified reduction, tunnelling, tailoring and suggestion, self-monitoring, surveillance, and conditioning as the most commonly used tools. **Tunnelling** provides a simple, sequential path for users to complete tasks in minimal time and reducing uncertainty, uploading data from a wearable exercise device such as a *fitbit*®, being an example. A **reduction** technique compresses a number of tasks into one streamlined step that shortens the path to the satisfaction of a goal, the Amazon "1-click" to shop being an example. **Tailoring** or customization is a technique that designers can use to learn more information about an individual in order to tailor offers or services to their exact needs, recommender tips from online shopping systems such as Amazon are an example of this. **Suggestion** techniques act as behavioural triggers, often using machine algorithms to learn from previous interactions with the user(s) and those others with a similar profile to pre-emptively suggest a course of action, offer information, and reminders that are based on an individual user's circumstance, usage history and/or profile. For example a text message from an exercise monitoring online network that prompts a user to engage in exercise as there has been a time lag between exercise bouts in a prescriptive plan. From an ecommerce perspective, populating a browser-based system with recommendations for footwear and clothing suited to the exercise most uploaded by a user. **Self-monitoring** as provided by devices and integrated services such as *fitbit*® enable goal setting and management and feedback process needed for self-regulation which in turn mediates self-efficacy. **Surveillance** techniques at a system level may include online social network group membership that affords members the opportunity to monitor the activities, goal realizations, dialogue, and geo-presence (location) of other members in the group thereby acting as a powerful social support and normative influence mechanism. This functionality is common in services such as *Nike Plus®, Suunto movescount®,* and *I Map my Fitness®* that are web-based software services enabling users of product specific devices in the case of Nike® and Suunto® or generic exercise data collecting devices in the case of I Map My Fitness® to upload their data, set and manage goals, share experiences, join similar interest or activity groups, analyse exercise efforts and manage their exercise lives.

Conditioning techniques used in BCSS are congruous with traditional extrinsic motivation techniques of reward and recognition with the system providing positive reinforcement of target behaviours; online services such as *EarnedIt®*. This service offers redeemable material rewards for users of online exercise systems to encourage their exercise persistence.

BCSS Evidence Base

Oinas-Kukkonen & Harjumaa (2009) ran a three-month-long qualitative field trial, exploring how a training program in a new prototype heart rate monitor promotes proper exercising. A framework for evaluating and designing persuasive systems was used to identify distinct strategies and techniques that were embedded within the system. Users' responses to these strategies were explored. The theoretical framework they used to evaluate the system was Persuasive Systems Design (PSD), a key element of BCSS. They found that some functionalities of the training program were effective in general terms and eventually influenced the behaviour of almost all users. The results of the study suggest that *goal setting, tracking performance, adopting social roles and high overall perceived credibility may all influence user behaviour*. The effectiveness of system-generated praise and reward via the feedback function was inconsistent across the participants. Although this study identified the potential utility of BCSS and PSD to gauge the persuasiveness of a technology to influence a behaviour change (exercise increase), it used a small sample size of twelve participants and measurements were entirely based on qualitative methods alone and did not make use of the exercise data. BCSS has until recently lacked any kind of standardised scale for determining the presence and or levels of functional elements of the model and had until very recently relied entirely upon observation and interviews of users. There are now a growing number of studies using validated BCSS-scales (Lehto et al., 2013; Stibe & Oinas-Kukkonen, 2014) in addition to a growing volume of research that investigates the validity and applicability of BCSS to behaviour change challenges based on sound empirical methodology.

Lehto & Oinas-Kukkonen (2011) examined the persuasive features of six web–based weight loss systems using the PSD theoretical model as an analysis template and found the sites were deficient in their implementation of persuasive strategies and techniques. While self-monitoring, rehearsal, and simulation functionality were strongly represented for effective primary task support; tunnelling, reduction, and tailoring were lacking. Dialogue support was poor and concerns were raised over systems credibility and verifiability. There was inconsistent application of reminders and suggestions to users across the sites. The study may be viewed as a promising start to building an evidence base for BCSS but it was severely limited by way of small sample size, homogeneity of problem representation and an analysis of function based on the authors' subjective views only. Kelders et al., (2012) reviewed the literature on web-based health interventions to investigate whether intervention characteristics and persuasive design affect adherence to a web-based intervention. With one hundred papers covering eighty-three interventions, the evidence base is substantial. It found, in terms of primary task support, that tunnelling is used most extensively and self-monitoring is predominant in lifestyle-health-based interventions but reduction and simulation were seldom used. For dialogue support, reminders are the most common elements used followed by suggestion. Praise was not used in any of the interventions and rewards were used only in three interventions. In social support, social facilitation is most often used; social learning and social comparison are used reasonably frequently while the other social influence elements (normative influence, competition, and recognition) are less regularly used.

Stibe & Oinas-Kukkonen (2014) explored how social influence design principles changed customer engagement in sharing feedback. The authors used a purpose-built information system designed according to BCSS principles deployed on public displays and used by seventy-seven Twitter users. They *found that that the seven social influence design principles of BCSS explained more than half (52%) of the variance in the perceived persuasiveness of the system* which further can predict forty-percent of the variance in the behavioural intention of participants to provide feedback through the system in the future. The main direct contributors that explained the variance in perceived persuasiveness were found to be normative influence, social learning, and competition. A challenge for other researchers is to extend the application of BCSS to other problem domains and system types, across both personal and public spaces. *For frameworks such as BCSS to be effectively applied in health behaviour change interventions, it needs to align as unobtrusively as possible with established systems design and development methodologies* whilst delivering applicable behaviour change functionalities, a requirement highlighted by (Harjumaa & Muuraiskangas, 2013). This work focused on the design, development and functional updates (based on BCSS-PSD principles) of a fall risk assessment system and a mental health mobile app where PSD was used to identify and implement new persuasive functionality. (Harjumaa & Muuraiskangas (2014), subsequently admit that the BCSS-PSD model falls short of being fully actionable in a software development project. It fails to provide translatable tools needed in the specification and validation tasks and is devoid of the practical means for engaging business domain experts and end-users in the development process. (Mohd & Shamsul, 2011) in a meta-review of critical success factors in software engineering projects identified accessible appropriate development processes or methodology and effective user engagement as important. Clearly, BCSS is lacking in this regard but as it is a relatively new model the lack of translatable mechanisms is to an extent, understandable.

Previously, an investigation by Lehto, Oinas-Kukkonen, and Drozd (2012) constructed and tested a model to predict the perceived persuasiveness and usage of a behaviour change support system. Their results supported a number of hypotheses about factors that may affect persuasiveness and actual usage. The final model is proposed as a meta-model suitable for use in studying health behaviours; clearly, it may require substantial testing, validation, and evolution across a number of domains and study designs before widespread adoption. The study finding that participants ascribed a virtual coach status to the device and its software may have implications for subsequent investigations into how these systems could better deliver virtual coaching that could positively influence exercise adherence.

BCSS in contrast to FBM is making progress toward creating both an evidence base and a theoretical framework that can be applied to empirical assessment tasks and practically deployed across multiple problem domains. It still has to be integrated into modern software engineering methodologies in order to be applied more widely.

Summary of BCSS Theory and Application

In effect, BCSS encourages analysis of the ***context*** in which the intended system is to operate, acknowledging the intent of the system in terms of what kind of change in behaviour is desired, the problem domain landscape, the characteristics of the target users and the strategy in terms of message and route the system design will use. Against this context, BCSS provides a matrix of ***design features*** for the designer to apply based on assessable theoretical constructs that can be operationalized as features of a persuasive system. This summary is depicted in Figure 9.

	PERSUASIVE DESIGN FEATURES			
PERSUASION CONTEXT	**PRIMARY TASK SUPPORT**	**DIALOGUE SUPPORT**	**CREDIBILITY SUPPORT**	**SOCIAL SUPPORT**
The Intent	*Reduction*	*Praise*	*Trustworthiness*	*Social learning*
Persuader	*Tunneling*	*Rewards*	*Expertise*	*Social comparison*
Change type	*Tailoring*	*Reminders*	*Surface credibility*	*Normative influence*
The Event	*Personalization*	*Suggestion*	*Real world feel*	*Social facilitation*
Use context[a]	*Self-monitoring*	*Similarity*	*Authority*	*Cooperation*
User context[b]	*Simulation*	*Liking*	*Third party endorsements*	*Competition*
Technology context[c]	*Rehearsal*	*Social role*	*Verifiability*	*Recognition*
The Strategy				
Message				
Route				

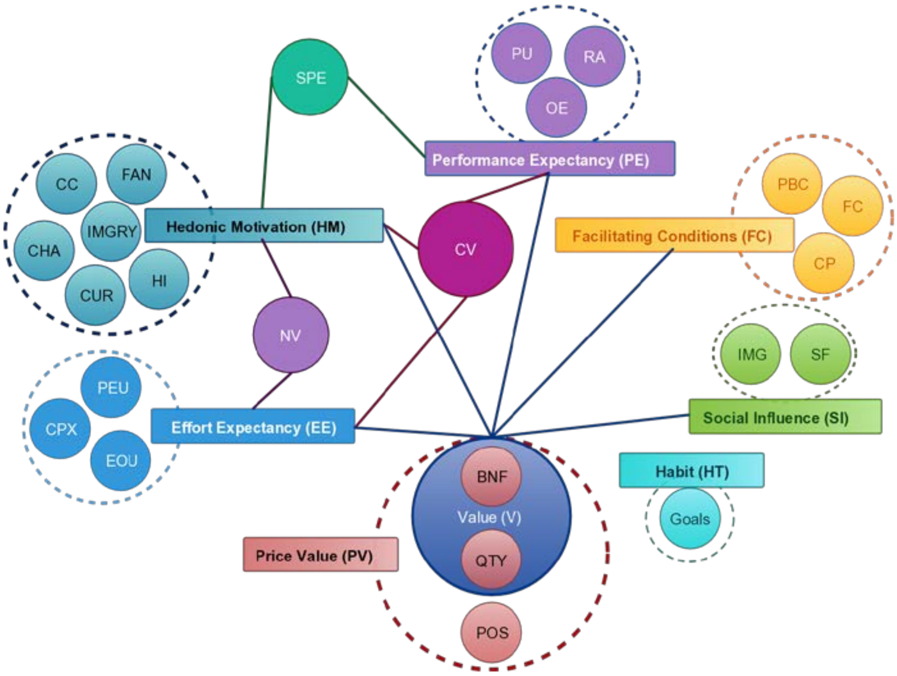
[a] Problem domain dependent features
[b] User dependent features e.g. goals, motivation, lifestyles, and others
[c] Technology dependent features

Figure 9. BCSS Theory Summary of Critical Elements.

Adapted from (Lehto & Oinas-Kukkonen, 2011). "Persuasive Features in Web-Based Alcohol and Smoking Interventions: A Systematic Review of the Literature". Journal of Medical Internet Research, 13(3), e46. Reprinted with permission. Copyright – Creative Commons Attribution License.

The Unified Theory of the Acceptance and Use of Technology

Venkatesh, Morris, Davis, & Davis (2003) devised the Unified Theory of Acceptance and Use of Technology (UTAUT) to explain the intention and usage behaviours of users of information technology. The theory holds that four key constructs; performance expectancy, effort expectancy, social influence, and facilitating conditions are direct determinants of usage intention and behaviour. **Performance expectancy** is defined as the degree to which an individual believes that using the system will help him or her attain gains in job performance; **effort expectancy** is defined as the degree of ease associated with the use of the system; **social influence** is defined as the degree to which an individual perceives that important others believe he or she should use the new system and **facilitating conditions** are defined as the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system. The UTAUT is an extension of the Technological Acceptance Model (TAM), a widely used theoretical model framed to explain potential users' behavioural intentions to access a technology or a new system (King & He, 2006). Venkatesh, Thong, & Xu, (2012) extended the original model to accommodate the broader context of consumer technologies, software applications, and services. In so doing, the four constructs were altered to embrace consumer use contexts. UTAUT posits that performance expectancy, effort expectancy, and social influence directly influence behavioural intention to use a technology, while behavioural intention and facilitating conditions determine the actual use of the technology. The individual difference variables of age, gender, and experience are expected to moderate the component relationships of UTAUT.



Overview Figure 8. UTAUT-2 overview.

From UTAUT2 (Venn Diagram) by D.Collahuazo, (2014) .. Retrieved from http://creately.com/diagram/example/hptzkm4j/UTAUT2. Reprinted with permission.

To address the application of UTAUT beyond corporations and institutions, Venkatesh, Thong, and Xu (2012) extended the model to produce UTAUT-2, illustrated in Figure 12 which demonstrated that when predicting continued use of IT, UTAUT predictors along with the addition of hedonic motivation, price value, and habit play important roles. **Hedonic motivation** is defined as the fun or pleasure derived from using a technology, and it has been shown to play an important role in determining technology acceptance and use (Brown & Venkatesh, 2005). Heijden (2004) examined the differences in user acceptance models for utilitarian and pleasure-oriented (hedonic) information systems. He found that *perceived enjoyment and perceived ease of use are stronger determinants of intentions to use information technology (IT) than perceived usefulness*. Venkatesh et al. (2012), found it also to be more influential in a consumer use context than performance expectancy. They also discovered that the price value factor was also found to be instrumental in influencing

IT purchase and use. What is not yet evident in the literature is how germane the application of UTAUT-2 is to optimising the design and use of device-centred network technologies and wearable exercise sensors by consumers. Given these technologies have inherent utility for managing exercise and exercise prescriptions and a hedonic element for sharing physical activity efforts and adventures; UTAUT-2 may be usefully applied to the sector in order to better understand system usage behaviours. These physical activity tracking devices such as *fitbit*,® *Nike Plus*®, Suunto *AMBIT*®, adidas *mi-coach*® and *Jawbone*® among many others are all provided with affiliated online social networks and social influence may play a large part in systems purchasing and usage. The application of UT-AUT-2-based investigations would seem to have potential to help better understand user behaviour in this space.

These emerging models for the persuasive design of systems that are intended to positively guide and support healthy behaviour change make extensive use of social networks as a means to not only create brand loyalty by association with similar other users but also potentially to act as a mechanism to spread positive behaviour through information and interaction. To fully appreciate the utility of online social networks in the use of activity tracking systems for assisting exercise behaviour it’s important to understand their architecture, features and intent along with evidence of their efficacy.

Online social networks, quantified-self and physical activity

The following table summarises the main studies, their investigative topics and resultant findings for this research area.

Table 4 Summary of Literature Review for Online Social Networks, Quantified-self and Physical Activity.

Study	Topic	Finding
McPherson, Smith-Lovin, & Cook (2001)	Role of social network homophily and behaviour.	The flow of behavioural and cultural information across a social network is largely localised and that network distance has as its corollary the distance between social relationships which in turn mediates the number of relationships through which an information piece needs to traverse in order to connect two individuals.
Centola & Macy (2007)	Social network properties and the spread of complex information contagions	Behaviour change such as adherence to an exercise intervention for managing a health condition is a complex contagion, requiring repeated contact and multiple points of social reinforcement and validation. This means the redundancy in tight networks that leads to wasted signal transmissions for simple contagions may be of benefit for the diffusion of complex contagions.
Foster, Linehan, Kirman, Lawson, & James, (2010)	Sharing exercise data online	Those who share exercise performance data online enjoy a significant increase in daily step count over peers who do not have access to the socialised data from the system.
(Zhang et al., 2013)	Ontological analysis of physical activity tweets.	Despite Twitter being promoted as and understood to be a social network, only 9% of tweets comprised content attesting to social support.
(Vickey, Ginis, & Dabrowski, 2013**)**	Analysis of exercise tweet content	Comments on exercise workouts via tweet were comparatively infrequent.
(Pagoto et al., 2014)	Online vs offline social support foe exercise intervention	Online social support for weight loss from Twitter friends more positive than offline support.

Social networking service (n.d) defines a social network as:

A platform to build social networks or social relations among people who, for example, share interests, activities, backgrounds, or real-life connections. A social network service consists of a representation of each user (often a profile), his/her social links, and a variety of additional services. Most social

> *network services are web-based and provide means for users to interact over the Internet, such as e-mail and instant messaging. Some social networks have additional features, such as the ability to create groups that share common interests or affiliations, upload or stream live videos, and hold discussions in forums. Geo-social networking co-opts Internet mapping services to organize user participation around geographic features and their attributes. There is a trend towards more interoperability between social networks led by technologies such as OpenID and OpenSocial. In most mobile communities, mobile phone users can now create their own profiles, make friends, participate in chat rooms, create chat rooms, hold private conversations, share photos and videos, and share blogs by using their mobile phone.*

Kaplan & Haenlein (2010) explain social media technologies as being ordered along the lines of social presence, content richness, and self-disclosure; a **Collaborative project** such as Wikipedia fosters the co-creation and publishing of information; **Blogs** provide information representative of an individual or single entity; **Content communities** such as YouTube and *Pinterest* share multimedia content with minimal self-disclosure; **Social network sites** *(SNS)* such as Facebook are high on self-disclosure and are media rich, particularly with built-for-purpose software applications ("apps") proliferating on such systems that allow for external service providers to leverage the social networking and security features of the SNS platform.; **Virtual Game Worlds** enable collaborative gaming, are rich in media and social presence, but low in disclosure.

Foster (2010) in a comprehensive study of motivation for Facebook use, comprising 2471, 18 to 30 year olds, discovered five key motivators that influence participation in a SNS; *friendship connections*; *information value*; *participation confidence*; and *participation concerns*. Krasnova, Spiekermann, Koroleva, & Hildebrand (2010) examined the motivators of information disclosure exhibited by

StudiVZ® and Facebook® users and found that site enjoyment is a prime driver of disclosure. They also found that the rewards gained from intense dialogue online negate the risk of excessive disclosure, aided by the trust in the respective systems' privacy and security functionality. For a health and exercise practitioner, the nature of OSN in particular and social media in general may be potentially game changing. With health data and conversations evolving in a global online world that exhibits the emergent, self-organised nature of an adaptive system; the mindset of health promotion planners, funders, and practitioners may need to evolve with this (Norman, 2012).

Online Social Networks and Health

Smith & Christakis (2008) believed *social networks influence health including physical activity* through a number of mechanisms, including *the provision of social support, social influence* as expressed through norms, sanctions and controls, as well as personal engagement such as conversation and access to resources such as knowledge and tools. *Online networks are not complete facsimiles of an individual's real world or offline social network.* McKenna & Bargh (2000) identified four key differences for self, identity relationships, and interactions that need to be considered when looking to understand and use online social networks: (i) there is potential for greater anonymity, (ii) there may be less emphasis on physical appearance, (iii) there is less emphasis on location and (iv) the greater control over the time and pace of interactions by the individual as an OSN user. Centola (2013) insists that the explosive growth in online social networks and social media channels stands to not only revolutionise health behaviour monitoring, but also the nature and potential applicability of these systems for research purposes. He classifies online social networks as either **Open Social Networks** or **Intentionally Designed Social**

Networks; this is a limited assessment. Intentionally designed social networks can be further classified based on membership criteria and purpose, suggested as follows, in Table 5, in relation to health-related applications.

Table 5 *A Suggested Online Social Network Classification. (Centola, 2013)*

Type of online social network	Examples
Open social networks	Google+, Facebook, Twitter, LinkedIn, Flickr
Condition-specific social networks	PatientsLikeMe
Device-centred social networks	SUUNTO MovesCount, NIKE PLUS, adidas mi-coach, Runkeeper, fitbit

Condition-specific social networks such as **PatientsLikeMe** foster a dynamic peer-to-peer exchange of treatment experiences, patient information, and practitioner experiences of patients, knowledge, and social support types. This type of online community aims to break down communication barriers, thwart social isolation and drive knowledge exchange. **Device-centred social networks** provide software services including mobile phone apps, online social networks, and an ecosystem for third party software developers to integrate value-added software applications using an open application-programming interface (API). These software services enable the collection of data from in-situ exercise-centric sensor devices such as pedometers, GPS trackers, heart rate monitors and wireless electronic scales and the publication of this data to the online social network where it is managed, archived, searched, analysed, shared and commented on. Such systems eliminate self-reporting bias and offer a first-hand view of social interactions specific to health behaviours and makes the measurement of key social factors such as homophily, clustering of connections and degree of connectivity simple and reliable.

Centola, in an investigation of social media and health behaviour, pointed to the specific shortcomings of traditional experimental methods in providing robust, scalable, and realistic results from social network behavioural studies, as seen in Table 6.

Table 6 *Comparison of Methods for Studying Social Influence on Health Behaviours. (Centola, 2013)*

	Traditional observational data	Laboratory experiment	Digital observation data	Internet experiment
Scale	√	X	√	√
Measurement	X	√	√	√
Structural control	X	√	X	√
Replication	X	√	X	√
Behavioural fidelity	√	X	√	√

It is to matters of scale; measurement, structural control, replication ease and behavioural fidelity that Centola believes the advantages lie for online social networks for health behaviour studies. On the question of scale, he points to the limitations of laboratory settings for providing a meaningful number of interactions between participants as a means for studying belief formation, social influence and behaviour change. For measurement ease, the built-in systems-based data provided leaves an indelible footprint of logins, connections, uploads, interactions and rich content that is time-stamped, archived, secure, and immutable – a huge advantage over more traditional methods of data collection. In contrast to the artificially constructed behaviours and social interactions of a laboratory setting, online social networks provide an increasingly seamless and transparent conduit for real-world online and offline behaviour with little discernible difference between these as online networks meld increasingly with daily life. This reasoning instigated the procurement and analysis of the large dataset used as the fulcrum for the thesis investigations.

Centola further argued that *observational studies struggle to control population structures*. Consequently, such an environment makes it difficult to causally identify those social factors that mediate changes in health behaviours. By contrast, in an online social network, all of the relevant interactions, rich content, alerts, and contacts germane to an observable behaviour can be archived and analysed. These *online social networks are also amenable for use in rigorous randomised control trials as discreet populations can be dosed with varying interventions and social and behavioural outcomes monitored and measured with easy and accuracy*. As Centola observes: " …replication has traditionally eluded empirical studies of social dynamics. The reason is that most large-scale observational studies cannot be reproduced under identical structural circumstances, with the same measurement capabilities, and with equivalent distribution of subject populations" (p. 2138). Online social networks are poised to play a role in health behaviour change but not without researchers and practitioners gaining insights into the dynamics of social networks as small worlds and how these particular dynamics can be exploited to effect positive behaviour change that can potentially scale up across population groups.

Social Networks and Diffusion

Information diffusion refers to the rate at which information is released and spread within a network and the reach of that same information. Yang & Counts, (2010) in examining how topics propagate through network structures across Twitter, developed three measurable dimensions of information diffusion in the Twitter social network: these are (i) **speed,** whether and when the first diffusion instance takes place; (ii) **scale**, the number of affected instances in the first degree; and (iii) **range**, how far the diffusion chain can continue on in depth. In their study of Twitter, *they found that the mention rate of the person tweeting information is a strong predictor of all three aspects of information diffusion through social networks in Twitter*. In

Twitter, as opposed to other online social networks such as Facebook, all content is public and Twitter users opt to "follow" (subscribe to receive that person's tweets) others based on content but without necessarily knowing the other person. Twitter, with 500 million registered and 200 million active users (Statista, 2013) is amongst the largest examples of a social network premised largely on what Granovetter (1973) terms "weak ties", (Virk, 2011). Those who constitute weak ties in an individual's social network are not well known; they tend to be casual acquaintances yet they do act to connect remote points on that same network. These ties contrast sharply with what are known as "strong" or "close ties;" these are people well known to an individual such as close friends and family. Close ties tend to be familiar with each other's friends and form triangles of association within the network; this is shown in Figure 11.

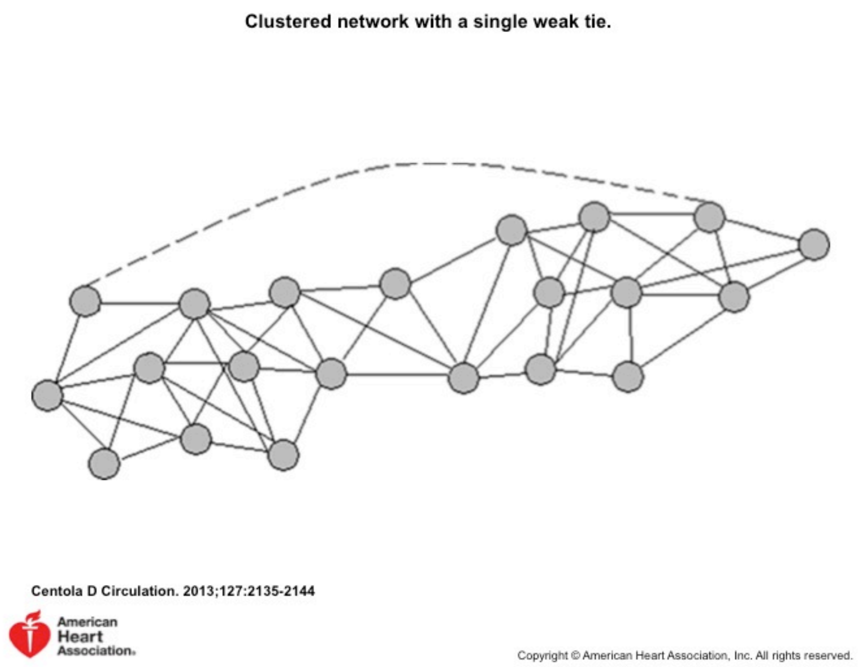


Figure 11. Clustered network with a single weak tie.

Adapted from "Social Media and the Science of Health Behaviour" by Centola 2013, Circulation, 127, p.2139. Copyright 2013 by the American Heart Association.

Close ties in a network tend to repeat transmission of the same information content within their tight connection triangles, repeatedly. *Weak ties* on the other hand, *are more likely to transmit the same information content to unknown contacts* resulting in social contagion being better able to exponentially reach other contacts than if the information had been transmitted to close ties only. Further to this, (Watts & Strogatz, 1998) examined small-world models of social networks, demonstrating the efficacy of low redundancy networks in the rapid spread of social contagions. Taking this work further, (Watts, 2004) demonstrated that random rewiring of a few ties in a clustered social network could dramatically lift the rate of information diffusion for a social contagion. This is shown in Figure 12.

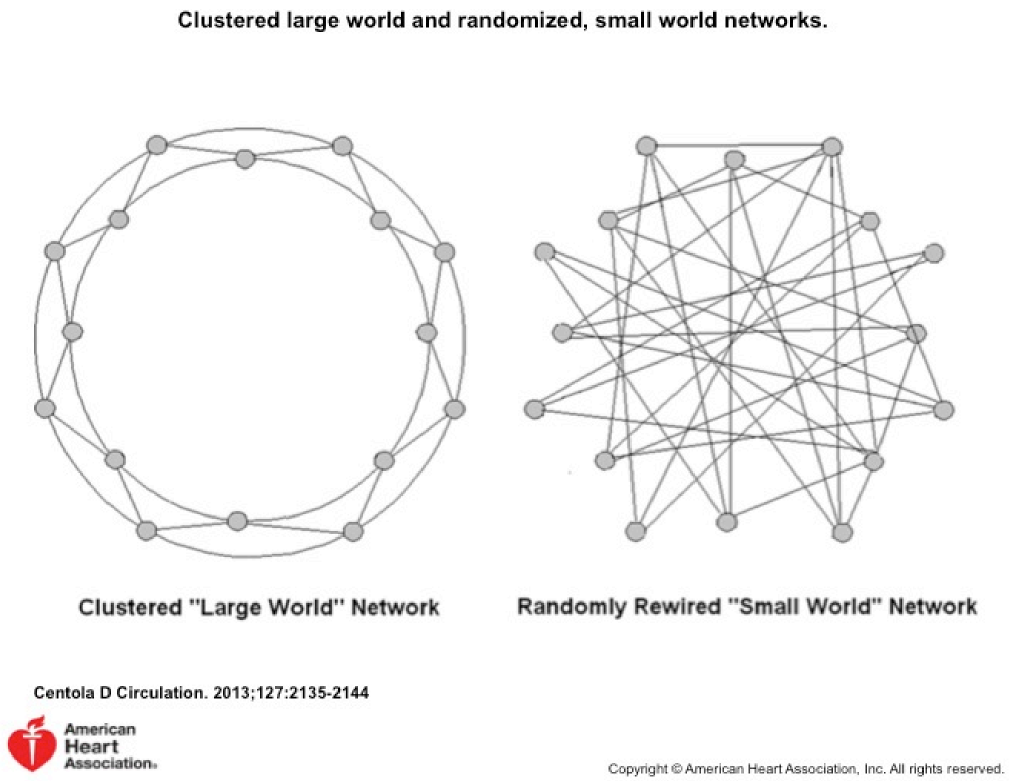


Figure 9. Clustered large world and randomised small world networks.

Adapted from "Social Media and the Science of Health Behaviour" by D. Centola 2013, Circulation, 127, p.2140. Copyright 2013 by the American Heart Association.

As shown in Figure 12, in a clustered lattice-based large-world network, the number of links to transit from one node to another randomly is to the order of the network size (N). However, if links in this type of network structure are randomly rewired and reassigned, the transit time between any two nominated nodes on the network will be reduced. Centola, Macy, & Egiluz (2005) discovered that random links between otherwise distant nodes can greatly facilitate the propagation of a disease or information, provided contagion can be transmitted by a single active node. However, when the propagation requires simultaneous exposure to multiple sources of activation, called *multiplex propagation*, the effects of random links are the opposite: it makes the propagation more difficult to achieve. These phenomena have potential implications for the diffusion of health information and behaviour change in real world social networks such that low-redundancy, fast-diffusion networks may ameliorate the uptake of positive health behaviour change such as exercise.

There is some evidence that behaviours related to weight management are socially transmissible; (Eisenberg, Neumark-Sztainer, Story, & Perry, 2005) found that social norms within one's peer group, but also at the larger school level, may influence unhealthy weight control behaviours, particularly for average weight girls. Christakis & Fowler (2007) examined the phenomenon of person-to-person spread of obesity in an adult population over a time period of thirty-two years, and found clear evidence that obesity appeared to spread through social ties. In the instance of structured PA, it is the type of social influence (peer, parents) and the type of setting (structured, unstructured) that affect PA participation levels. The evidence points to social influences playing a primary role in the adoption of healthy and unhealthy behaviours.

Centola & Macy (2007), using their complex contagions model, revealed that social network structures that facilitate rapid diffusion of information and disease could impede the spread of behavioural contagions. The authors argue that the relative simplicity of disease and information as contagions lends them to be transmitted by a single contact with the contagions. Behaviour change such as adherence to an exercise intervention for managing a health condition is a far more complex contagion, requiring repeated contact and multiple points of social reinforcement and validation. This means the redundancy in tight networks that leads to wasted signal transmissions for simple contagions may be of benefit for the diffusion of complex contagions. The authors went further, demonstrating that reduction in redundancy leads to obliteration of channels required for social reinforcement. According to Centola (2013):

> "*...behaviours spread faster and produce overall greater adoption when travelling through clustered social networks with redundant ties than when travelling through the putatively more efficient small world networks.…….the more complex the social contagion is, the more that successful diffusion depends on clustered triangles in the social network.*" (p. 2140).

Social support can mediate the diffusion of behaviour change across a population as well as in an individual. What is not yet in evidence whether this model-based proof of specific health behaviour change diffusion can be optimised with live online social networks, either open networks, condition-specific networks, or device-centred networks. Given the body of evidence in favour of established health behaviour change theories such as SDT, and others being effective in eliciting positive clinical outcomes, there may need to be consideration of both these theoretical models and network design models when health practitioners design and deploy complex contagion in online social networks.

Smith & Christakis (2008) maintained that to better understand the role of social networks in influencing health behaviours, consideration of the presence of selection and **homophily –** *the tendency of individuals to associate and bond with similar others – on networks* must be given. McPherson, Smith-Lovin, & Cook (2001) found peoples' personal networks are homogeneous with regard to many sociodemographic, behavioural, and intrapersonal characteristics. This homophily mechanism is instrumental in determining that the level of contact between similar people exceeds that of dissimilar people. This means that the flow of behavioural and cultural information across a social network is largely localised and that network distance has as its corollary the distance between social relationships which in turn mediates the number of relationships through which an information piece needs to traverse in order to connect two individuals. Centola (2011) examined the behaviour of participants in an online fitness program based on an intentionally designed social network. They looked at the impact of rearranging social relationships based on homophily in the adoption of an online dieting tool by the participants. Homophily significantly improved adoption in the overall population of the online community and specifically among the obese members of the program. *Homophily in an online social network devoted to fitness significantly increased the adoption of new health behaviour*.

Social Networks and Homophily

De Choudhury, Sundaram, John, Seligmann, & Kelliher (2010) investigated the relationship between information diffusion in an open social network (Twitter) and the presence of homophilous relationships along shared attributes of users such as their location, information roles, or their activity behaviour. The work quantified and demonstrated that *attribute homophily influences the diffusion process in an online social network (Twitter)* with the diffusion characteristics mediated by the metric used to quantify the diffusion effect and the information topic under consideration. Location attribute-based homophily provided an ability to predict topological diffusion features including reach and that activity - behaviour-based homophily attributes that reflect the temporal profile of user tweeting can predict diffusion characteristics for tweets addressing external events such as sports, politics, and events. Along with the opportunity to mingle online with those of like mind and interests, OSN also provide a conduit for individuals to express themselves and present their characteristics, interests, accomplishments, and activities to others.

Social Networks and Physical Activity

Exactly how an exerciser behaves and what motivates them, how persistent they are and how well basic psychological needs are satisfied offline may be a logical starting point for understanding how they transpose this through the data, exercise outcomes and social interactions generated when they upload their exercise data online. Analysis of current research literature shows that application of health behaviour change models assists adherence to exercise interventions (Weinberg & Gould, 2010). These models identify the crucial role of intrinsic motivation through enhancing autonomy, competence, or self-efficacy, and the relatedness to and social support of significant others (Ryan et al., 1997). If a mechanism for social support is missing from an exercise intervention program, its efficacy may suffer; for example, a lack of relatedness and social support can deprecate performance of college football teams (Garland & Barry, 1990). *Social support is seen as a recurrent predictor of exercise adherence in most studies of intervention effectiveness* (Sherwood & Jeffery, 2000). DiMatteo (2004), in a review of the literature from 1948 to 2001, identified 122 studies that demonstrated a correlated structural or functional social support with patient adherence to medical regimens. Meta-analyses established significant average *r* -effect sizes between adherence and practical, emotional, and unidimensional social support. Oka et al., (1995) examined the types of social support that best predicted adherence at different time points during a 1-year endurance exercise program in 269 women and men aged 50 to 65 years. Results indicated that *social support specific to exercise was a better predictor of exercise adherence than general social support*. Increasingly, in a world that is ever reliant upon information and communication networks and enabling technologies such as smartphones, wearable sensors, and social media to connect it, social networking sites (SNS) such as Facebook and Twitter have become salient social support environments, with frequency of social media shown to be related to wellness and perceived relationship with family (Asbury & Hall, 2013).

Facebook and Physical Activity

Webb, Joseph, Yardley, & Michie (2010), in a review of Internet-based interventions promoting health behaviour change, found enough evidence to justify investment in further investigative work that is based on established behavioural change models and techniques. Munson (2011) reflected on an active learning investigation he conducted with colleagues using Facebook-based software. They sought to better understand and qualify the use of Facebook apps for positively influencing individual wellness. Users benefited from the social support and information exchange the systems offer. *The most effective members of the group using the Facebook app are those the user already has a strong social connection with*. Three benefits users found with the Facebook apps for wellness management6

(i) making a good impression, (ii) inspiring others and (iii) connecting with family and friends specifically around wellness activities. This study is limited in its rigour and protocol and provides little direction or verifiable evidence that would enable practitioners to justify effort and resources being invested into wellness management through Facebook. A subsequent study (Cavallo, 2012) indicated that participants in a randomised control trial to assess a physical activity social support intervention primarily delivered through Facebook will join and exchange important types of social support for physical activity using online social networks. This study used a very simplistic intervention lacking any substantive software functionality over and above what Facebook itself delivers it also encapsulated no traceable implementation of specific behavioural change theories.

The potential of Facebook as a delivery conduit for PA interventions has gained recent attention, a study by (Valle, 2012) assessed whether an existing SNS (Facebook) is an effective channel to deliver a physical activity (PA) intervention to young adult cancer survivors. In contrast to other recent investigations, this study employed a rigorous design protocol and thorough analysis, finding that in all participants, social support from friends and self-monitoring were positively associated with changes in moderate-to-vigorous PA. The proposed psychosocial mediators (self efficacy, social support, and self monitoring) that were assessed using standardised scales did not explain the positive effect of the intervention on mild PA. Concluding that a SNS may be an effective means for promoting mild PA among young cancer survivors, there was no proof of causation. Neither of these studies from 2012 made use of exercise data, clinical measures, implementation of health behaviour change basics (goal setting, tools for eliciting and encouraging autonomous motivation), or shared visualisation of progress.

There is an explosive global growth in the use of fitness devices, apps, and online services, with ABI Research predicting that the wearables market is poised to create 485 million users by 2018, (Comstock, 2013) and one in ten people over the age of eighteen in the USA own a fitness device from the major market providers as at September 1 2013, (Ledger & McCaffrey, 2014). Such phenomenal growth of dedicated physical activity social networking systems that publish, share, and manage the exercise and lifestyle activities of individuals has shown that a lack of evidence does not impede the investment of entrepreneurs in the promise of socially networked exercise data for wellness management.

However, *are there measurable benefits to be accrued from the use of these technologies in targeted health and exercise interventions?* If so, what is the best method of investigating and substantiating possible benefits and applications of these systems? How can researchers and technologists integrate proven health behaviour change models into the software used by these systems and how can such systems be realistically applied to community health and wellbeing challenges cost-effectively? There exist proven instruments and protocols for assessing changes in key behavioural change elements pre and post intervention, including the examination of autonomous motivation, competency, and relatedness to others under the auspices of the SDT. It is perhaps a question of now applying rigour to the problem space. What substantive research has been finished to date has been primarily based on simple pedometer-based devices in conjunction with integrated Facebook-based management and monitoring apps.

There is an abundance of multi-indicator sensor devices capable of publishing and sharing to social networking systems advanced clinical data, these include blood glucometers, blood pressure sensors, skin temperature sensors, and heart and respiration rate sensors. Along with providing a conduit for individuals to connect to others for the sharing of information and exercise data, social networking sites or systems (SNS) such as Facebook®, Nike Plus®, Runkeeper®, Suunto Moves Count®, and Endomondo® can provide support for groups of individuals sharing a common physical activity, interest or chronic condition using these devices with multiple sensors. There is emerging, very early *evidence of social networking sites playing a modest, positive role in health behaviour change interventions* according to a recently published meta-analysis (Laranjo et al., 2014; Maher et al., 2014).

Twitter and Physical Activity Behaviours

It is a common function of digital exercise devices to publish an exerciser's session data to the Twitter social network. There is to date scant evidence to draw upon for assessing the relevance of the two related technologies to exercise-centred interventions. Kendall, Hartzler, Klasnja, & Pratt (2011) in a major study of physical activity commentaries on the Twitter social networking platform, found that the two most frequent categories were posts in which users reported evidence of or plans for exercising. Given the explosive rate of adoption of SNS, including Twitter—which has doubled from 35% of Internet users in 2008 to 61% in 2010 (Lenhart, Purcell, Smith, & Zickuhr, 2010)—there is emerging both a critical mass and communications multiplex that may provide a globally scalable social support framework that enables health behaviour change (Kendall et al., 2011).

Williams, Hamm, Shulhan, Vandermeer, & Hartling (2014), in a meta-analysis of social media interventions for diet and exercise behaviours involving randomised controlled trials, identified only 22 relevant studies making use of Twitter as part of an intervention; these trials revealed low levels of participation and did not show significant differences between groups in key outcomes. There has been at least one example of a social-media-based exercise intervention study (Nishiwaki et al., 2013) that aimed to clarify the effects of a lifestyle intervention by the concurrent use of an activity monitor and Twitter on daily physical activity. The authors found that the lifestyle intervention delivered through the concurrent use of an activity monitor and Twitter could effectively induce an increase in daily physical activity compared with the intervention using only an activity monitor. This work is severely limited in terms of generalized applicability by the small homogenous sample size. Another small-scale study by (Turner-McGrievy & Tate, 2013) examined the role of Twitter in a remotely delivered weight loss intervention. They found that engagement with Twitter was related to weight loss and participants mainly used Twitter to provide *information support* to one another through status updates.

A larger, more inclusive investigation of the adoption and spread of a core-strengthening exercise through an online social network (Pagoto et al., 2014a) surveyed users who joined during the first two months of an exercise-a-day challenge to describe their characteristics, including social support for exercise and to what extent they invited others to join. The study continued to track total users for 10 months. Participants reported that online friends provided as much positive social support for exercise as family and in-person friends. The authors concluded that *online social networks might be a promising mechanism to spread brief exercise behaviours*. The inference from this study is *that social media and online social networks show promise*, of a yet to be validated nature and extent, in lifestyle-based health interventions, particularly *around delivery of* an *online* variant of *social support.*

Subsequent to this work, (Pagoto et al., 2014b) explored the role of online and offline social networks on the weight loss activities of 100 adult females. It was found that the participants felt their Twitter friends were greater positive influencers and less negative influencers than their offline social networks, family, friends, and Facebook friends when it came to their weight-loss efforts. The key benefits those who tweeted during weight loss programs experienced were social support, information and being held accountable. However, the brevity of Twitter's communication mode of 140 characters and its impersonal environment, lacking true connectedness and relatedness were regarded as impediments.

Zhang et al., (2013) explored the use of Twitter as a potential tool for promotion of positive health behaviours by analysing over 1 million public tweets about physical activity in the USA over a 90-day period. Publishing information (97.6%) and discussing and opining (90.27%) about physical activity were popular among the dataset. Despite Twitter being promoted as and understood to be a social network, only 9% of tweets comprised content attesting to social support. Those users with fewer followers and with fewer accounts that they followed (followings) were more likely to talk positively about physical activity on Twitter whereas those with more followers were more likely to publish neutral comments about physical activity and individuals with more followings were more likely to forward tweets to others.

To frame an appropriate approach that seeks to best use of potentially useful social media mechanisms that could encourage physically active lifestyles, a detailed understanding of their design, structure and their engagement processes are required. By necessity, this entails knowledge of offline social networking principles along with established psychosocial theoretical frameworks and network modelling science. There has however, been some initial progress in better understanding exercise tweets themselves as researchers play catch up with publicly available social media data.

Vickey, Ginis, & Dabrowski (2013) examined over two million exercise tweets resulting in a demonstrable text classification model for Fitness Tweets as illustrated in Figure 13.

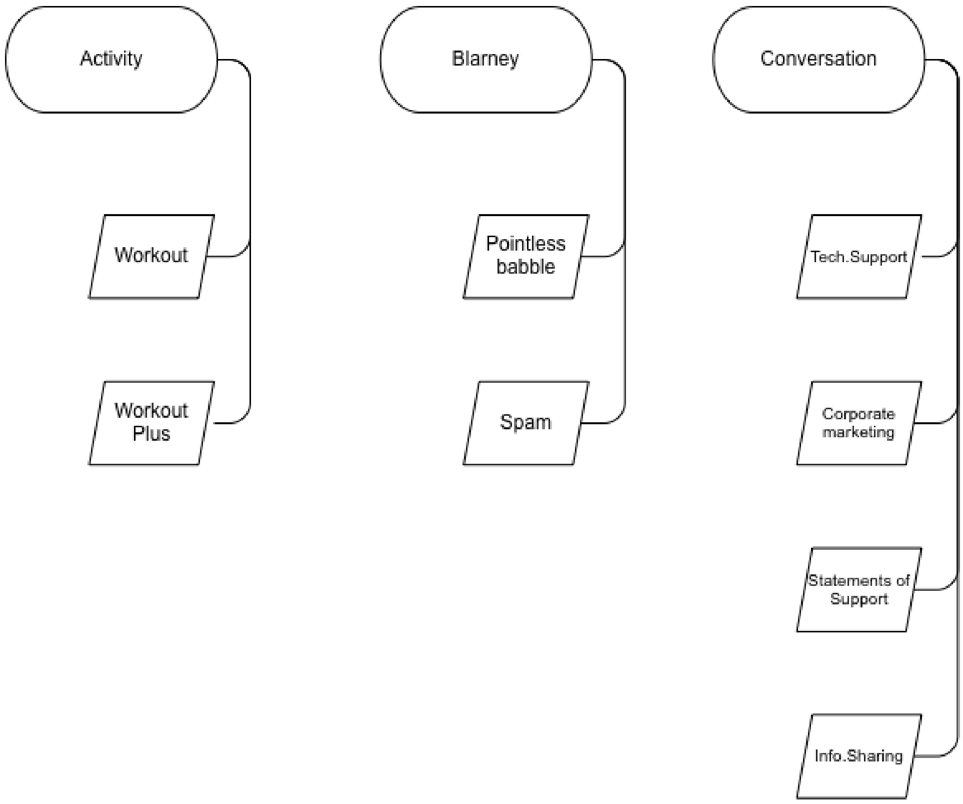


Figure 13. Vickey-Breslin tweet classification model.

Adapted from " Twitter classification model: the ABC of two million fitness tweets", by T.A.Vickey, K.M.Ginis, & M.Dabrowski, Translational Behavioral Medicine, 3, p.308. Copyright ©2013. Reprinted with permission.

Using this approach to analyse the over two million tweets in their dataset, they found that 73% of all tweets were for Activity (an actual published exercise session), being 52% workout (actual data from their device) and 21% workout plus (additional commentary about the exercise session); 21% were conversation-based tweets and 5% were what was termed blarney (light-hearted banter not germane to the exercise itself) in nature. Overall, they concluded that *conversations about workout tweets were a relatively small portion of tweet traffic*. Additionally, they queried the motivation of users to use the publish-to-Twitter functionality of their exercise devices given their lack of tweet dialogue around these published workout sessions. Given its generic system functionality, a publish-to-Twitter function seems it may be secondary to the prime ability for users to publish to their device vendor's own social network of similar (exercise) users. This may be because the social interaction requirements of the user are better met by this primary, closed peer-based social network of common interest (exercise) i.e., homophilous network than a large, open, and public social media space such as Twitter. Further investigation is required to determine the validity of this speculation.

Social Influence

Kahan (1997) defined social influence as "consciously or subconsciously persuading others from your thoughts, beliefs or actions" (p. 364). Aronson (2004) deems it as occurring when others affect one's emotions, opinions, or behaviours. Interestingly, the levels of individual social influence differ, (Katz & Lazarsfeld, 1970).

In an online setting, the ability to identify, understand, engage with and possibly support and encourage key social influencers of positive health behaviour may be an effective strategy to assist in community-level health behaviour change (Centola, 2013). The ability to identify Twitter users has become key to firms looking to increase product and service sales and positively manage company and brand image online (Cha, Haddadi, Benevenuto, & Gummadi, 2010; Ghiassi, Skinner, & Zimbra, 2013). Identifying influencers and encouragers from within an individual's social network was seen to be positively associated with motivation to change dietary and physical activity behaviours among adults of Mexican origin (Ashida, Wilkinson, & Koehly, 2012). Carron, Hausenblas, & Mack (1996) found in a meta-analysis that social influence factors have a small to moderate positive effect on exercise behaviours of adherence and compliance

Cha et al., (2010) compared three different measures of influence—indegree, retweets, and mentions[1] — based on the analysis of 1.8 billion tweets from almost 55 million users. Indegree is treated as a means for assessing user influence based on the size of that user's audience. Retweeting reflects the influence generated by the pass-along value of a user's tweets and mentions indicate how the proclivity for social engagement and conversation manifest in the system. They found that popular users with a high level of indegree do not necessarily catalyse many mentions and retweets. Irrespective of topic, the top users on Twitter consistently display a disproportionately large influence and this was found across the more prominent categories including celebrities and large media firms. To gain and maintain influence, the data showed that a user has to sustain their engagement with the platform, making full use of its tweet, retweet, and mention functions on a regular basis.

To determine, track, and share an individual's online social influence, a swathe of influence ranking services have emerged, foremost among these being Klout®, PeerIndex® and Kred®. It is usual for these services to display a Twitter user's social influence score as part of their profile. The algorithms used to determine these arbitrary scores have not been made available for scrutiny by dispassionate third parties. It is unclear what role, if any such a scoring service may play in affecting the social influence of individuals who may publish their exercise behaviour to Twitter, a function that is common to the most popular exercise tracking systems. More

[1] Indegree is the number of people who follow a user; retweets mean the number of times others "forward" a user's tweet; and mentions mean the number of times others mention a user's name.

fundamentally, are there any identifiable trait(s) of those individuals who may exert greater online social influence in their use of OSN that can be used to encourage non- and infrequent exercisers to be more physically active? Can we identify these people through published Tweets from digital exercise tracking systems?

The proliferation of OSN has coincided with the rise of wearable devices for tracking physical activity and health vital signs. This mass produced technology brings with it the facility to self-monitor not only exercise, wellbeing and social and emotional dynamics but also clinical measures such as blood glucose levels and blood pressure, all in-situ. This next section of the review looks to better understand what drives people to use this technology and pieces together a small but growing body of evidence that points to what works and what doesn’t when using the systems to aid individuals in using physical activity as a means to improving health.

The Quantified Self Movement and Self-Monitoring

The following table summarises the main studies, their investigative topics and resultant findings for this research area.

Table 7. *Summary of Literature Review for Self-Monitoring and Physical Activity.*

Study	Topic	Finding
McPherson, Smith-Lovin, & Cook (2001)	Role of social network homophily and behaviour.	The flow of behavioural and cultural information across a social network is largely localised and that network distance has as its corollary the distance between social relationships which in turn mediates the number of relationships through which an information piece needs to traverse in order to connect two individuals.
Centola & Macy (2007)	Social network properties and the spread of complex information contagions	Behaviour change such as adherence to an exercise intervention for managing a health condition is a complex contagion, requiring repeated contact and multiple points of social reinforcement and validation. This means the redundancy in tight networks that leads to wasted signal transmissions for simple contagions may be of benefit for the diffusion of complex contagions.
Foster, Linehan, Kirman, Lawson, & James, (2010)	Sharing exercise data online	Those who share exercise performance data online enjoy a significant increase in daily step count over peers who do not have access to the socialised data from the system.
(Zhang et al., 2013)	Ontological analysis of physical activity tweets.	Despite Twitter being promoted as and understood to be a social network, only 9% of tweets comprised content attesting to social support.
(Vickey, Ginis, & Dabrowski, 2013**)**	Analysis of exercise tweet content	Comments on exercise workouts via tweet were comparatively infrequent.
(Pagoto et al., 2014)	Online vs offline social support foe exercise intervention	Online social support for weight loss from Twitter friends more positive than offline support.

The advent of multi-function, wearable exercise performance sensors and accompanying smartphone software applications (apps) that integrate with social networking sites (SNS) have taken PA self-monitoring to new levels of sophistication and reach. Evidence-based research into the efficacy and effects of such technology across the community including exercise involving the obese and pre-diabetes is in a nascent state.

Much of the momentum driving widespread adoption of these technologies has been attributed to what is known as the **Quantified Self Movement or Personal Informatics**. This movement positions itself as a nexus of *collaboration between users, designers and manufacturers of data and devices used for self-monitoring*. Without definitive analysis it is difficult to determine an exact demographic or psychographic profile of Quantified Self (QS) users but given the cost of the most common devices, the computer literacy needed to use the device to full effect, and the education required to understand and apply the gathered data to health and well being, it is probable that affluent, early adopters have been at the forefront of the movement.

Lee (2014), in a study of QS Meetup Group member presenters, discovered their primary motivations for involvement were its alignment with personal interests and a concern for personal health. Little more is known about the users of QS technology such as physical activity trackers and their supporting software environments; their types of psychological needs, behavioural drivers, social interactions on and offline; or the design of the systems themselves and what part it plays on usage or persistence.

According to (Fox & Duggan, 2013), in an extensive survey of free-living adults, 69% of U.S. adults track a health indicator like weight, diet, exercise routine, or symptom. Of those, 50% track "in their heads," one-third keep notes on paper, and one in five use technology to keep tabs on their health status. Trackers living with multiple chronic conditions are more likely to be methodical about collecting their own health data:

- 45% of trackers with 2+ conditions use paper, like a notebook or journal, compared with 37% of trackers with 1 condition and 28% of trackers who report no chronic conditions.
- 22% of trackers with 2+ conditions say they use a medical device, like a glucometer, compared with 7% of trackers with 1 condition and 2% of trackers who report no chronic conditions.

Thirty-four percent of trackers say they share their records or notes with another person or group, either online or offline. Of those, a little more than half (52%) share with a clinician. Not surprisingly, trackers who do not take formal notes are less likely than others to say they update their records on a regular basis or to share their progress with someone else. Trackers with chronic conditions are significantly more likely to report that these activities have had an impact on their health; 56% of trackers living with 2 or more conditions say it has affected their overall approach to maintaining their health or the health of someone they help care for, compared with 40% of trackers who report no chronic conditions.

Certainly, based on this qualitative analysis and the rapid growth of participation in online health and exercise social networks, with the Nike Plus® system reputedly hosting over 11 million users globally (Laird, 2013), the self-monitoring "movement" is widespread. Currently, there is no detailed analysis available to explain the type of devices used, the frequency with which they are used, the primary and secondary purposes to which these devices are used, or how the data from these devices are used to augment or integrate with primary or specialized health care providers and their systems or processes.

Until there is a substantiated body of scientific evidence, researchers have to contend with a mountain of online opinion pieces upon which to start analysis although, (Goetz, 2013) provides one of few contrary pieces to the majority view of blind, enthusiastic editorial support for the Quantified Self movement. In placing diabetic self-monitoring under critical scrutiny, Goetz references a qualitative study (Hortensius et al., 2012) that investigated how patients with type 1 and type 2 diabetes find the burden of self-monitoring their illness. Lowered self-esteem and increased anxiety and depression went hand-in-hand with many of these patients. The points drawn by the author is that a section of the population, mandated by health practitioners to self-track and manage their disease condition, find it a daunting and difficult task. He points to the innately complex and invasive blood sampling and analysis process itself, the inefficient ergonomics and poor software interface design of common glucometers and the sheer isolative experience of coping with a major illness. In recommending a way forward, Goetz provides a three-point strategy to attempt to improve the diabetic experience of self-monitoring:

> "*First, self-tracking needs to be as effortless and automatic as possible; friction is the enemy. Second, the tools need to be designed with the consumer in mind, not the clinician. The best practices of consumer electronics need to be applied, and the data needs to be kept in the background whenever possible. And third, it's essential that self-tracking address the emotional needs of the patient, not just their rational side*." (para. 10)

Without evidence of a comparative study in the literature, it's difficult to speculate as to what the differences in persuasive design emphasis needs to be between chronic health monitoring systems and digital exercise systems and what features they should have in common.

Cooper & O'Gorman (2011) recommend the development of accurate monitors to objectively measure spontaneous physical activity and energy expenditure and that such devices be able to create personalized daily recommendations that are easy to use. The manner in which personal informatics data is portrayed by self-monitoring technologies to the user is essential to the understanding of the data, usage satisfaction, and enabling of target behaviour and persistent use of the technology to manage prescriptive application (Consolvo et al., 2008; Lin, Mamykina, Lindtner, Delajoux, & Strub, 2006; Pavel, Callaghan, & Dey, 2011).

Self-Monitoring

The need to defray public health costs and share the burden of care with individuals and their immediate support networks has been assisted in its uptake as a policy initiative by the proliferation of self-monitoring technologies, processes and knowledge. Self-monitoring spans a broad range of health conditions and intervention models covering clinical disease and lifestyle management. Ruckenstein (2014) recently investigated the use of heart rate monitors and data visualisation from a perspective of self-optimisation and defined self-monitoring as:

> *"A practice that seeks to make known something that is typically not a subject of reflection, with the aim of converting previously undetected bodily reactions and behavioural clues into traceable and perceptible information. Consequently, the design and technical specifications of tracking technology builds on the notion that visibility is desirable and that it is of value for people to have their physiologies and everyday movements made observable and legible."* (p.69)

There exists a dearth of solid research into the effects of self-monitoring of physical activity on self-efficacy, health behaviour change and the increase of exercise behaviour in the general population. Gleeson-Kreig (2006) looked to determine if there was a difference in outcome of physical activity (PA) levels between individuals who maintained six weeks of self-monitoring and recording of physical activity and those that did not.. She found that the self-monitoring and recording intervention resulted in enhanced self-efficacy and that PA improved in both the intervention and control groups. Unfortunately, there was no collection and analysis of critical health and exercise measures using pre and post-test processes. There was no quantitative data collected from participants performing their physical activity. This limitation makes it difficult to understand whether or not there were any clinical benefits from using self-monitoring and recording. What is valuable to consider is the positive effect self-monitoring and recording had on self-efficacy. Gleeson-Kreig makes a cogent argument for explaining a possible mechanism of influence on self-efficacy through the use of self-monitoring activity; it encourages enactive attainment through feedback to the individual of behaviour and outcomes using visual means and acts concurrently as a tool for social persuasion. There may be scope for the self-monitoring feedback loop of digital exercise tracking systems to tap into a virtuous cycle relationship with health practitioners, advisors, and peers. This assertion could be examined using the BCSS-PSD framework to identify the key social influence, social learning, and social identification features of these systems.

Self-Monitoring and Adherence to PA Interventions

Recent work shows people who use simple pedometer-based devices in conjunction with seamlessly integrated Facebook based management and monitoring software that enables sharing of performance data enjoy a significant increase in daily step count over peers who do not have access to the socialised data from the system (Foster et al., 2010). Hurling et al., (2007) showed a fully automated web/mobile phone-based monitoring, motivation, and social support system can increase and maintain the level of physical activity in healthy adults. Munson, Lauterbach, Newman, & Resnick (2010) demonstrated that embedding a wellness-specific software intervention in Facebook is a viable option for improving adherence rates compared to other Internet-based wellness interventions. None of these studies have either measured or discerned the behavioural factors behind the observed improvements in PA and PA adherence using these technologies. Exactly how does the software provide support for the behavioural elements of health change and how can such mechanisms be observed in action, then measured and improved upon?

Functional software features that enable visualisation of exercise performance and progress could encourage enactive attainment and of course, the dynamics of SNS-based self-monitoring services may provide a rich environment for social persuasion. Consolvo, Everitt, Smith, & Landay (2006) investigated whether technology could encourage physical activity by providing personal awareness of activity level and mediation of physical-activity related social interaction among friends. The researchers compared the percentage of days on which goals were met between groups sharing their individual data and those who kept that data to themselves, in an endeavour to determine the influence, if any, of data socialisation. The group sharing their data was assisted by a more advanced version of the baseline software used by both groups, with additional features such as messaging and commentary on the step counts of others and the facility to see the progress of others towards reaching their activity goals. The sharing groups were significantly more likely to meet their goal. All but one of the participants was motivated by social influence with social pressure, support, and communication being the chief classes of influence. *The group with access to those software functions that enabled and supported such social influences experienced higher levels of goal realisation*.

The evidence base that explains the level and types of interaction, discourse, or engagement that supervene use of the Facebook social networking platform particularly for self-monitoring of PA, is in a nascent state. What research has been done shows some promise. The ability to publish physiological data from exercise sensors to social networking platforms may have a positive influence on the accomplishment of performance-specific goals for clinical users and recreational athletes. Hurling et al. (2007) evaluated the impact of a physical activity program based on the Internet, Bluetooth-enabled wrist-worn accelerometers, and mobile phones with 77 healthy adults over a 9-week period. Participants were randomized to a test group that had access to the technology-based physical activity program replete with peer-to-peer message board, electronic reminders and real-time web-based feedback or to a control group that received no technology or support. The test group performed substantially better than the control group with greater improvements against baseline for intention and expectation to exercise and perceived control

There was a higher level of moderate physical activity in the test group. The work showed a fully automated web/mobile phone-based monitoring, motivation, and social support system can increase and maintain the level of physical activity in healthy adults.

Foster et al. (2010) completed a study to determine whether interactions between users via the StepMatron, a Facebook application designed to provide social and competitive context for daily pedometer readings, prompted more successfully motivated physical activity than simply recording daily step counts in a similar application. The study involved ten registered nurses (nine females and one male), all of them employed within the same hospital ward and personally known to each other as friends. To determine whether the social interaction element of the application was necessary over just recording and displaying feedback, the researchers created two conditions—socially enabled and non-social. In the former condition, participants could view each other's step data and make comparisons and comments. In the non-social condition, participants were restricted to viewing their own personal step data. The study design used modified crossover to circumvent any ordering effects. As a consequence, each participant experienced both conditions. The study found that *the participants with* ***socially enabled*** *access who could view their colleagues step data and make comparisons and comments had significant increase in step activity over the other participants in the non-social condition*. This finding may point to a positive relationship between social interaction over an online social network and the motivation to increase physical activity in a work-based setting. Given the relative homogeneity of the study sample and small number of participants, the outcomes may have limited scope for application across at-risk, free living people with diagnosed metabolic conditions such as impaired glucose tolerance.

There is evidence that *self-monitoring of physical activity greatly increases long-term adherence to regular exercise*, which in turn is associated with greater improvements of risk factors and quality of life (Arrigo, Brunner-LaRocca, Lefkovits, Pfisterer, & Hoffmann, 2008; Izawa et al., 2005). Maitland and Chalmers (2010) pointed to the outcomes of the (Zutz, Ignaszewski, Bates, & Lear, 2007) study that used a web-based cardiac rehabilitation programme known as *vCRP* to deliver reduced risk factors and increased exercise capacity in an intervention group, as evidence of promise for self-monitoring in cardiac care. From their own cardiac rehabilitation programme study, they emphasised *the salience of designing for both the social and clinical contexts of the user*.

Given the explosive growth of self monitoring for heath and exercise it's easy to lose sight of what the evidence tells us from before the advent of the technology about what exactly works in optimising exercise adherence and why. The next section looks to expose what is known about effective exercise adherence strategies as they may still be of use in the design of persuasive systems for activity tracking.

Exercise Adherence

The following table summarises the main studies, their investigative topics and resultant findings for this research area.

Table 8. *Summary of Literature Review for Exercise Adherence*

Study	Topic	Finding
McPherson, Smith-Lovin, & Cook (2001)	Motivation and exercise adherence.	Self-efficacy and self-motivation as key individual attributes that affect optimal adherence levels; competence and self-belief are also consistent factors in predicting longer-term exercise adherence.
Weinberg & Gould, 2010, (Chan, Ryan, & Tudor-Locke, 2004)	Group exercise training.	Tackling an exercise program on your own as opposed to working with a group has been found to lessen adherence and enjoyment and increases the level of challenge for the solo trainer
Jennings (2010)	Successful exercise interventions for hypertension treatment	Factors to consider in order to optimise adherence; research-proven methods, tailoring interventions to the individual, setting realistic targets and key progress milestones and clearly and consistently communicating the reasons for the program and the methods or approach used

For exercise interventions, adherence refers to the extent that exercisers follow prescriptive program processes and session patterns to completion (Oman & King, 1998). Oman & McAuley (1993) explored the relationship between intrinsic motivation and exercise behaviour in participants participating in an eight-week aerobic fitness program. Prior to and following the program, intrinsic motivation was measured, it was found to be significantly associated with attendance and participant's confidence in their intentions to continue exercising post-program, and thus adherence. The more prominent health behaviour models including SDT and (SCM), point to self-efficacy and self-motivation as key individual attributes that affect optimal adherence levels; competence and self-belief are also consistent factors in predicting longer-term exercise adherence, (McAuley, Jerome, Elavsky, Marquez, & Ramsey, 2003). Clearly then, *exercise participants are more likely to adhere to prescriptive programs if they enjoy task mastery and competence along with autonomous motivation.*

Any exercise prescription designed to invoke substantial change in physiological variables be it for health or performance sport can be challenging. Tackling an exercise program on your own as opposed to working with a group has been found to lessen adherence and enjoyment and increases the level of challenge for the solo trainer (Weinberg & Gould, 2010). A consistent conclusion by researchers of group exercise interventions has been that the individual's attraction to a group, and the group's exercise-based task, is associated with increased adherence to an exercise program (Annesi, 1999). Other research has addressed social aspects of sharing information about activity and found that exercising together can also motivate individuals to do more activity; people increase their activity level as they engage in light competition (Chan, Ryan, & Tudor-Locke, 2004). Stephens and Craig (1990, as cited in Annesi, 1999, p. 544) concluded most adult participants would prefer to exercise with others rather than alone; and Massie and Shephard (1971, as cited in Annesi, 1999, p 544) found group-based program attendance exceeds individually based programs.

As King and colleagues (1997) and Jennings (2010) discuss, the variables that directly influence physical activity levels do not operate in isolation from one another; they are interdependent. Jennings (2010), in studying successful hypertension interventions, derived a list of important factors to consider in order to optimise adherence, which include choosing effective, research-proven methods, tailoring interventions to the individual, setting realistic targets and key progress milestones and clearly and consistently communicating the reasons for the program and the methods or approach used.

Optimising adherence may also require attention to the volume and fidelity of any exercise prescription. Perri et al., (2002) investigated the effects on adherence of prescribing exercise at moderate versus higher levels of intensity and frequency. They found that prescribing a higher frequency of exercise increased the accumulation of exercise without a decline in adherence. In contrast, prescribing a higher intensity level of exercise decreased adherence and resulted in the completion of less exercise. A contributory factor to the poorer performance of the high intensity group was found to be a higher incidence of exercise-related injuries experienced by this group. An important feature of this study was the use of sedentary rather than active or high-performance athletes as participants. There may be a reduced level of exercise-induced injury in more active participants who enjoy greater fitness levels as well as a pre-existing conditioning base and concomitant mental and physical preparedness. Certainly, the promise of detailed, up-to-date tracking of individual exercise effort by duration, intensity and frequency afforded by activity tracking systems may serve to help reduce fatigue-induced injury, illness and abandonment in exercisers. Exercise bout and effect can be tracked in real-time and changes made on the spot.

Summary of Evidence

Health behavioural change theories such as SDT and SCM, can be effectively applied to optimise exercise interventions for targeted health outcomes. Online social networking technology shows promise as a means to enable social support of exercise interventions and health behaviour change programs. Self-monitoring of physical activity, health and well-being using wearable sensors and their supporting software ecosystems may provide a manageable, scalable means to gather potentially useful exercise performance and health indicator information in near to real-time. This self-monitored information may be useful in assisting the implementation of sustainable nutrition and exercise programs for improving health, athletic performance, and wellbeing, particularly if use is made of proven health behaviour change theories. To increase the chances of individuals adhering to exercise programs, the activities must be enjoyable and opportunity provided for group support and social interaction. Exercise adherence also is more likely if the individual is autonomously motivated, enjoys task competence and is free to relate to others in that physical activity. The recent, explosive growth of digital exercise trackers and web-based quantified self-monitoring services (Vickey, 2014) has left research-based evidence lagging in its ability to validate the veracity of the efficacy claims of vendors marketing the technologies. As a result, there is a dearth of evidence-based guidelines for technology design that may optimise targeted exercise behaviours proffered by these device manufacturers. In BCSS, among other nascent behaviour change and persuasive systems theories, there has emerged a potentially sound theoretical framework for assessing and shaping the behavioural persuasiveness of self-monitoring technologies including digital exercise trackers.

Given the knowledge, evidence and methodologies gleaned from the literature there is ample scope to identify ways and means of empirically measuring, understanding, and modelling the behaviour of users of these exercise-tracking systems. There is, to date, no investigation of the users themselves, their behaviour as recorded by the systems' data management function, and their own views on how the system affects their exercise behaviour. The proposed set of studies looks to help bridge this gap in knowledge. A combination of quantitative and qualitative techniques will be applied to a large sample population of exercise tracking system users, from a commercial vendor's database source. This is intended to help us to better understand the demographic and anthropometric attributes of these individuals and how they interact with the system and other users in their pursuit of satisfying exercise behaviours. Of particular interest is the role that online and offline social interactions may have on their system usage and how persistent they are in the use of the technology over time (12 months). The evidence points to the role systems design may have on persuading individuals to behave in a preferred manner (Lehto, Oinas-Kukkonen, & Drozd, 2012; Oinas-Kukkonen, 2013; Thieme et al., 2012). Attention should be paid to the operationalization and systems-enabled satisfaction of the relatedness to others psychological need, a key factor of SDT (Wilson et al., 2003) and a need that often requires satisfaction in order to motivate people to start and sustain exercise.

Research Gaps Pursued

The study was inspired in the greater part by the overwhelming growth of activity tracking wearables in the consumer space and concomitant hyperbole that amongst other things claims the technology will enable wholesale changes to public health and wellbeing. It aims to cut through the hype and answer some fundamental questions about who uses these wearables, how they use them and what affects their persistent use with particular attention on their software design and its relationship with established theories of health behaviour change.

In particular, the work looks to bridge an existing gap in the characterization of the exercise behaviour of a population of fitness device users along with their social interactions and possible correlations between the two. It also looks to break new ground by understanding how users of an activity tracking system interact with the system design elements and the role such elements play in the relative persuasiveness of the system, which is to encourage exercise activity. The existing evidence reveals scant use of validated measurement scales to determine the efficacy of persuasive systems design on activity tracking systems.

The work looks to add to existing evidence by providing a structural model to articulate and help better understand the factors that may influence the online social activities and persistent device use of users of an activity tracking system. This should explain the associations between the design of the system and satisfaction of relatedness needs with others in physical activity (ROPAS – a scale used in SDT), online sociability and intended continued use of the system. Finally, the work endeavours to inform the literature of any understanding that may exist in associating exercise outcomes and the comparative online social influence of individuals that use activity tracking systems

Chapter 3
General Methods

Introduction

This chapter examines the methods used to source data then transform and prepare it to answer the specific research questions for each study. The chapters devoted to each discreet study details the research questions themselves, the preparatory and analytic methods used, the results of these methods are linked to each research question and a discussion of the meaning and relevance of the findings provided.

The overarching goal of the research, to inform the effective design of persuasive systems for exercise, also provides the connective tissue between the four studies completed. To articulate the direct links between the Thesis Goals, their Research Questions and the specific Studies that instantiate them, a Traceability Schema follows.

Schema Table 1 Traceability Scheme for Goals, RQs and Studies

GOAL	Goal description	Research Questions (RQ)	Study
1	Identify who are the users and what they do with the app, the device an done another.	**1**. What are the most popular types of physical activities recorded and uploaded by users of an activity tracker device to the vendor's online social network and exercise management service? **2**. What are the main demographic & anthropometric characteristics of the cohort as recorded by the activity tracking system? **3.** What level and type of online social interactions have occurred by and between individual members of the user population using the systems online social network? **4**. How many users publish their exercise sessions to Twitter, and what characterises these users demographically and anthropometrically? **5**.What association if any, exists between a user's anthropometric characteristics and their published moves in this system?	1

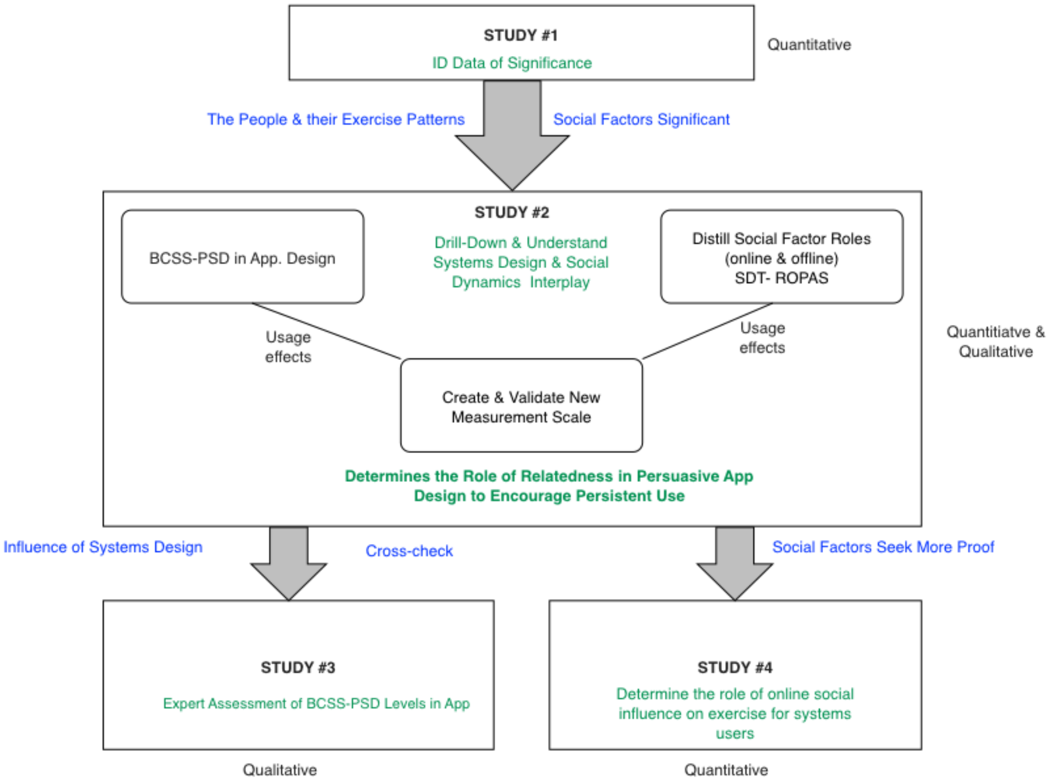
GOAL	Goal description	Research Questions (RQ)	Study
1	Identify who are the users and what they do with the app, the device an done another.	**6**. Do users who Create Groups or Belong to Groups login more frequently or exercise more frequently than other users?	1
2	Identify the attributes of the most persistent users of the system	**7**. Which users most frequently upload exercise sessions and persist the longest in using the device over time, and what characterises these users?	1
3	Identify the role of pre-existing exercise behaviour on intention to persist using the device	**8**. What portion of the sample population was actively exercising prior to purchasing the Suunto device and system? **9.** How regularly did users indicate they used the device as part of their normal exercise regime?	2
4	Create a new scale linking BCSS-PSD to SDT via the ROPAS scale.	**10.** What were the most popular functions of the movescount.com system in the sample? **11**. Does analysis of the movescount.com sample population responses to the BCSS scale reveal consistency with the existing evidence? **12.** Does an individual's Relatedness to Others in Physical Activity (ROPAS) score in any way predict the perceived social support and social identification functions of the system? **13.**. Is there a difference in the ROPAS scores between users who publish exercises sessions to Twitter and those users who do not?	2

GOAL	Goal description	Research Questions (RQ)	Study
4	Create a new scale linking BCSS-PSD to SDT via the ROPAS scale.	**14**. What part is played by the factors in the BCSS scale that assess the persuasive elements of the system on the users intention to continue using the system? **15.** Can we create a structural model that will represent the association between a user's intent to continue using the system, BCSS; persuasive systems design factors, key user demographics, exercise usage, online group membership and prior exercise behaviour?	2
5	Galvanize expert assessments of the level of PSD compliance in the *movescount* app.	**16**. How completely and effectively does the *movescount.com* system implement the recommended BCSS-PSD design techniques?	3
6	Determine the association between an individual's published *movescount.com* exercise moves to Twitter and their online social influence as calculated by the KLOUT service.	**17.** What demographic variables characterize the sample of Twitter users? **18.** Do those individuals who publish their moves to Twitter and revealing a higher online social influence (KLOUT) score demonstrates higher exercise effort measures by way of distance, speed, and training effect (TE)? **19.** Is there any association between those users who publish their exercise sessions using additional devices and services and their KLOUT score? **20.** Is there any association between those users who publish their exercise sessions using additional devices and services and their exercise effort measures?	4

The first study contains descriptive statistics for the sample of the Suunto user population as well as simple correlations between key usage factors;number of exercise sessions, use of social media, and anthropomorphic metrics. Given the uniqueness of the data, fairly detailed descriptive statistics are a prerequisite for determining whether structural equation models from the BCSS literature will be determinable. The second study augments the existing structural equation models in the BCSS literature by adding components intended to account for both the use of social media by device users and the effects of social media on exercise as we seek to understand the nature and extent of device and system usage as part of the daily behaviour of the individuals' surveyed. We decided the results of the structural equation models from study two could be used as an indicator of the potential for social media in the exercise space; the third study provides an expert panel's evaluation of SUUNTO's implementation of persuasive design as an independent source of that potential and indicates areas where design improvements could be realised.

The fourth and final study flows from the findings of study two. It is a quantitative analysis of public exercise tweets by users of the *movescount.com* activity tracking system to help us better understand the attributes of this group and the role, if any, of their online social influence rating or score (as calculated by the KLOUT.com service) on the frequency and intensity of their published exercise moves.

The connectedness between the studies is revealed in Overview Figure 3.



Overview Figure 3 How the Studies Interconnect: a schema. Copyright© D.L.Foy 2016.

Each study has a dedicated chapter with its own Introduction, Methods, Results, Summary of Findings and Discussion section. Each of these chapters also includes a description of the thesis goals being addressed and research questions answered by each study.

Study One: Quantitative Modeling of the Suunto Movescount Exercise Tracking System Sample User Population

Data Procurement for Study One

Explanation

The following vendors were approached in 2013 to participate in the study and allow secure, managed and legally constrained access to data from activity tracking datasets; NIKE, adidas, fitbit, Suunto and Jawbone. Only Suunto responded to the affirmative, despite persistent follow-ups with all parties. Its participation was deemed highly suitable given the global nature of its user population, the breadth and depth of data captured and the support of the study objectives. Given the quality and relevance of the dataset and the then rarity of such access given to researchers in this burgeoning problem space, supervisory advice was such that it was regarded as worthwhile, valid and valuable to base the first two major studies on this Suunto dataset.

Suunto Oy of Finland provided a live database export from their operational SQL-Server database in August 2013. Suunto is a producer of advanced digital exercise tracking devices, heart rate monitors and online software services including a social network and management system known as *movescount*.com. A cross section of the core system functionality for *movescount.com* can be found in Appendix I and a brief but insightful tour of the system and its features can be accessed online at http://www.movescount.com/tour

Users of the Suunto Ambit wearable device and *movescount* online software services generated the data used for this study; 20,000 members of this user population were used as the starting point for analysis. This data was extracted from the database according to a strict and exact selection filter based on user-member permission to use data for health research purposes. All individuals had made their data available based on a pre-existing legal agreement with Suunto. The procurement process was vetted and approved by the University of Tasmania Human Research Ethics Committee and documented in Appendix A. The data as exported by Suunto Oy in de-identified form was not in an immediately usable format for the purposes of error-free import into Stata version 13. As a result, the author was required to write an original mySQL program (script) to address the low level format issues present in the Suunto dataset, bearing in mind at no point was the data itself compromised by way of accuracy, validity or integrity either in its original or final file formats. The script produced, original intellectual property created as an artefact is included as Appendix D and was created and stored in mySQL Community Server 5.6.1 before being exported as a .csv file to Stata version 13 where it was then analysed for redundancy and validity by the investigator and data clean up procedures employed where necessary. All source data files are available on the media provided for examination of this thesis. Explanation of the data transformation process is detailed in Appendix D.

Data Preparation for Study One

The *movescount*.com data is the first proprietary fitness tracker data set to be made available for academic research. The data contain a breadth of variables well suited to the overarching research goal of gaining insight into the design of persuasive systems for promoting exercise. First, it contains a variety of demographics. Second, it includes activity type, date and duration, along with metrics associated with the type, duration and intensity of the exercise. In addition to these basic variables, the data set contain indicators of users' engagement in several different types of social interactions, including creating and/or belonging to groups of users, sending messages, (SHOUTS and THUMBS), the posting of feelings, and use of Facebook and Twitter. Outside of RCT data sets, no data set available to academic researchers has the scope of the *movescount*.com data for research on fitness tracker devices. Notwithstanding this breadth, a couple of limitations of the data should be noted. First, although each user's workout sessions are time-stamped, there are gaps in the time coverage. This has an impact on the study of persistence of exercise as discussed below. Second, although the number of people a user follows and the number following a user are known, the identities of who is following who are not known, which prohibits analysis of networks of users other than by the groups they belong to.

The source data as exported from the MySQL schema generated by the study script was organised into nine files addressing the major functions of the *movescount* system as follows:

1. Exercise-Community-User-Demographics
2. Exercise-Community-User-Anthropometrics
3. Exercise-Community-User-Followers-Following
4. Exercise-Community-User-Uploaded-Exercise-Sessions (a.k.a. *moves*)
5. Exercise-Community-User-Thumbs (equivalent of *Likes* in online social media)
6. Exercise-Community-User-General-Shouts (equivalent to comments on posts in online social media)
7. Exercise-Community-User-Shouts-at-Exercise-Sessions
8. Exercise-Community-Groups-Users-Belong-To
9. Exercise-Community-Users-Who-Created-Groups

Study Two: A Mixed Methods Modeling of Suunto Movescount Exercise Tracking System Sub-Sample User Population Responses to a Psychosocial Scale that Examines Persuasive Systems Design, Usage and Intention to Continue Use.

Recruitment of Participants for Study Two

The opted-in health research user database provided under agreement with Suunto Oy was used to recruit respondents to complete a survey form online. This form was designed to answer the pertinent research questions. An invitation to participate was emailed to all members of the opted-in database, a sample of which is included as Appendix G and electronic links included to the online survey form securely hosted by **SoGoSurvey.com**. No incentives were offered to prospective respondents as a lure to complete the survey. A total of 11,290 emails were sent of which approximately 7.5% were invalid or had deprecated after the original user registration with the system and 530 responses were received to create the sample, a response rate of 4.7%. The surveys were sent in week one of July 2014, and all responses were collated as Microsoft Excel (.xls) files following a cut-off date of July 31st, 2014 for all responses. The data set is completely discreet from that used in study one. The volume of the email dispatch was large and had to be separated into four even batches and a basic counterbalance employed as shown by the two instances of the survey form used and included in Appendix B. A simple counterbalance of the order of scales (not questions within scales) was carried out to see whether the order in which questions were asked had any effect on the answers.

Instrumentation for Study Two

The survey form used incorporated the standardised Relatedness to Others in Physical Activity Scale (ROPAS), (Wilson & Bengoechea, 2010), the BCSS-PSD scale for asessing the persuasiveness of health behaviour change systems, (Lehto et al., 2012) and the online sociability susbscale of the Brief Test of Online Behaviour (BTOB) by (Johnson & Kulpa, 2007). Questions were also asked to determine gender, education, type of predominant exercise behaviour prior to purchase of the device and system and to better understand how specific online software functions of the system are used. The theoretical constructs used to form a model based on the survey are detailed in Appendix K, Table K1.

The complete form is included in its initial and counter-balanced variant as Appendix B. Two different forms of the same survey were used in anticipation of a test of the reliability of the survey. We wished to mitigate a sample selection effect occurring in the groups that received the forms that may have lead to a confounding of group effects with reliability, so an assumption has been made that the instrument is reliable.[2] In addition to reliability, online surveys often raise concerns about sample selection because it seems reasonable to expect that more active users are more likely to respond to a survey request than less active users. However, the distributions of both login count and number of sessions (Moves) were nearly identical in the systems usage data files for demographics and exercise sessions (Moves) as in the survey data, so no weighting of the survey sample was necessary. In short, despite the presence of some sample selection effect in the groups who received each form of the survey, overall, the sample of survey respondents reflects population frequencies of login counts and number of moves.

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[2] Specifically, form A survey respondents had a mean login count of 0 versus 20 for form B and form A respondents had a mean of 0.06 exercise sessions versus 16 for form B. The items on the surveys have been field tested previously and appeared in several publications, so the assumption that they are reliable here seems warranted. Also, the only apparent difference in responses for the two forms is in login count and number of sessions (moves).

As detailed in the survey form reproduced in the Appendix B, the first four questions after the user's ID provide demographic information, including gender, birth date, marital status and education. The next two questions provide information on prior exercise, including whether the respondent was exercising in the 12 months immediately preceding purchasing the device and, if no, had they ever exercised regularly. The remaining survey items were either adapted from previous studies in behavior change support systems and exercise or developed specifically for this survey. In order on the survey, these items and the names used to refer to them below (in upper case) are the following:

- Relatedness to Others in Physical Activity Scale (ROPAS) (Wilson & Garcia Bengoechea, 2010)
- Behavioral Change Support Systems (BCSS) (Lehto & Oinas-Kukkonen, 2014)
- Online Sociability (O_SOC) a series of questions that indicates usage of the Internet for communications such as instant messaging and email developed by Johnson and Kulpa (2007).
- Device usage questions (USAGE) developed specifically for this survey and indicating how frequently users exploit various features of the device.

Data Matching from Study One and Study Two

The live systems usage data generated by the population sample used for Study One could in theory be matched by the unique *movescount.com* User Identification Number (UID) to the users who completed surveys used in Study Two. Additionally, selected data from the Moves files including counts of all activity in the social interaction functions of the system as well as login counts, number of moves and fitness index mean were merged with the survey data. There were a number of inconsistencies between the two data sets with respect to self-expressed usage frequencies and counts of usage frequencies. For instance, there are examples where a survey respondent indicates that they never make a shout, whereas they are counted as making 8 shouts in their actual recorded Moves data, a relatively large number. For several of the analyses that follow, the usage numbers for the Moves data were not significant predictors in regression equations when it was anticipated that they would be. The time lapse between the survey and the Moves data, which in most cases is six to twelve months, may be an explanation for this.

Study Three: An Expert Assessment of The System Implementation of BCSS-PSD Design Principles in movescount.com

A panel of five experts from the University of Twente experienced in the theoretical aspects and practical application of BCSS to the design, development and deployment of health behaviour change systems were engaged to complete an independent evaluation of the *movescount* system. It was also deemed important that the panelists were at least aware of the *movescount.com* app and have had used it or be able to learn to use it quickly for their own exercise efforts as part of their rating process in this study. This also required that they or their university had access to a suitable Suunto AMBIT exercise tracker to assess the *movescount.com* app. The panel that was selected fitted this requirement and was available and willing to participate in a timely manner. Other similar panelists were sought but only the five individuals that returned assessment documents responded to the affirmative.

Panelists were asked to rate BCSS design principle presence in the movescount.com app using a validated design assessment format as used by (Lehto & Oinas-Kukkonen, 2010). The rating process was completed in isolation from others; there was no collaboration.This task was made easier as the panelists were on vacation during the study period. They were asked to complete their ratings in 30 days. The experts independently scored the presence and degree of satisfactory implementation of PSD design principles, according to the theory and guided by the BCSS-PSD reference table included as Appendix C.

Study Four: An Examination of the Exercise Outcomes and Characteristics of Movescount Users and its Association with their Online Social Influence Scores.

Recruitment of Participants for Study Four

Active users of the Suunto system who publish their exercise moves as tweets to the Twitter social media service were identified using a common Twitter search #hashtag string known to be unique to this user community and their tweets archived using Hootsuite software. These public tweets were collected over a 28-day period and disassembled to identify and record exercise and online social influence scoring data. All user account identifying variables and data values for each and every Twitter user in this sample were removed to ensure privacy and anonymity. This data was then examined using Stata 13 via both descriptive and a variety of regression analysis techniques.

Chapter 4

Introduction

Study One is focused on learning about the key demographic and anthropometric characteristics of the users from the Suunto movescount.com population data provided. It also seeks to identify online social patterns of behaviour as captured by the core functions of the system, in particular Logins to the system itself, user tendencies in following the physical activity and actions of others in the system, the action of liking an uploaded exercise session, the activity of commenting on the activities of others and the tendency of users to join online groups of common interest. We also examine the exercise efforts of the user population.

Analyses are conducted to determine associations between the demographic and anthropometric characteristics, exercise outcomes and online social behaviours of users to identify any associations between these factors to answer the research questions and satisfy the relevant thesis goals.

Goals and Research Questions

Goal 1

Identify who are the users and what they do with the app & device and one another.

Research Questions

RQ1. What are the most popular types of physical activities recorded and uploaded by users of an activity tracker device to the vendor's online social network and exercise management service?

RQ2. What are the main demographic & anthropometric characteristics of the cohort as recorded by the activity tracking system?

RQ3. What level and type of online social interactions have occurred by and between individual members of the user population using the systems online social network?

RQ4. How many users publish their exercise sessions to Twitter, and what characterises these users demographically and anthropometrically?

RQ5. What association if any, exists between a user's anthropometric characteristics and their published Moves in this system?

RQ6. Do users who Create Groups or Belong to Groups login more frequently or exercise more frequently than other users?

Goal 2

Identify the attributes of the most persistent users of the system

Research Questions

RQ7. Which users most frequently upload exercise sessions and persist the longest in using the device over time, and what characterises these users?

Methods

The nine discreet source files processed in the data transformation step from the vendor database and identified in Chapter 3 were examined for this study sequentially and descriptive analysis conducted on each file to uncover key characteristics of the system users. To answer the specified research questions and matters of interest that arose the analyses were conducted as followed; précis of variables in each file, descriptive statistics of the file and correlation and regression analysis of target associations between variables within and across the data source files. Additionally, binomial regressions and CART analyses were conducted to examine persistence with the device amongst users.

To answer the Research Questions, correlation and multiple regression analyses were completed for the relevant variables in and between the nine data source files. All analytic work is implemented using STATA 13 other than the temporal analysis required to determine user persistence with the device for exercise, which was completed using R.

To answer the research questions for this study this sequence of methods was used.

1.1. Demographic descriptive data analysis

1.1.1.1. Regression analyses of demographic data including social media use with System Access (aka Login Count)

1.2. Anthropometric descriptive data analysis

1.2.1.1. Regression analyses of anthropometric data including social media use with Login Count

1.3. Descriptive Analysis of the Social Factor known as Following Users

1.3.1.1. Regression Analysis of Following Behaviour on the System and Login Count

1.3.1.2. Regression Analysis of Following Behaviour on Uploaded Exercise Sessions (aka Moves)

1.4. Descriptive Analysis of Moves

1.4.1.1. Regression Analysis of Moves and Login Count, Exercise Intensity Measures

1.4.1.2. Regression Analysis of Moves and Publish to Social Media

1.5. Descriptive Analysis of Affirmations for Moves

1.5.1.1. Regression Analysis Affirmations for Moves and Login Count and Number of Moves

1.6. Descriptive analysis of Comments (aka as Shouts) on Moves

1.6.1.1. Regression analysis of Shouts and Login Count and Moves

1.7. Descriptive Analysis of Groups

1.7.1.1.1. Those Groups users belong to (membership)

1.7.1.1.2. Those Groups users create (creation)

1.7.2. Regression analyses of Group Creation and Membership with Login Count and Number of Moves

2. **Panel Data Analysis of Persistence of Moves over Time** (who keeps exercising the longest with the system)

2.1. Binomial negative regression

2.2. Classification and Regression Tree Analysis (CART) of Move Persistence

The logical flow of nethod output to input for each of the following is detailed in the Results section.

Results

RQ 1

What are the most popular types of physical activities recorded and uploaded by users of an activity tracker device to the vendor's online social network and exercise management service?

RQ2

What are the main demographic and anthropometric characteristics of the cohort as recorded by the activity tracking system?

Demographics Analysis

The source data file comprises identifying information for a user common to any equivalent online identification profile, including gender; location, activity and social media account connectivity. Table C1 in Appendix C describes the demographics variables from this dataset. Appendix E contains the table output for Study One.

Table E1 (Appendix E) displays a summary of gender, the top 5 default activities, and social media usage, and Table E2 summarizes Age and Login count. The sample is heavily weighted towards females (*N* = 17,873, 89.36%). The most commonly specified activities were running (*N* = 6,902, 34.51%), cycling (*N* = 1,017, 5.08%), mountain biking (*N* = 754, 3.77%, and indoor cycling (*N* = 363, 1.81%). The most commonly used social media platform was Facebook (*N* = 2,204, 11.02%), followed by Twitter (*N* = 528, 2.64%). The average age was 39.03 (*SD* = 9.97), and the average login count was 7.37 (*SD* = 18.04). Figure 13 displays the frequency distribution of login counts.

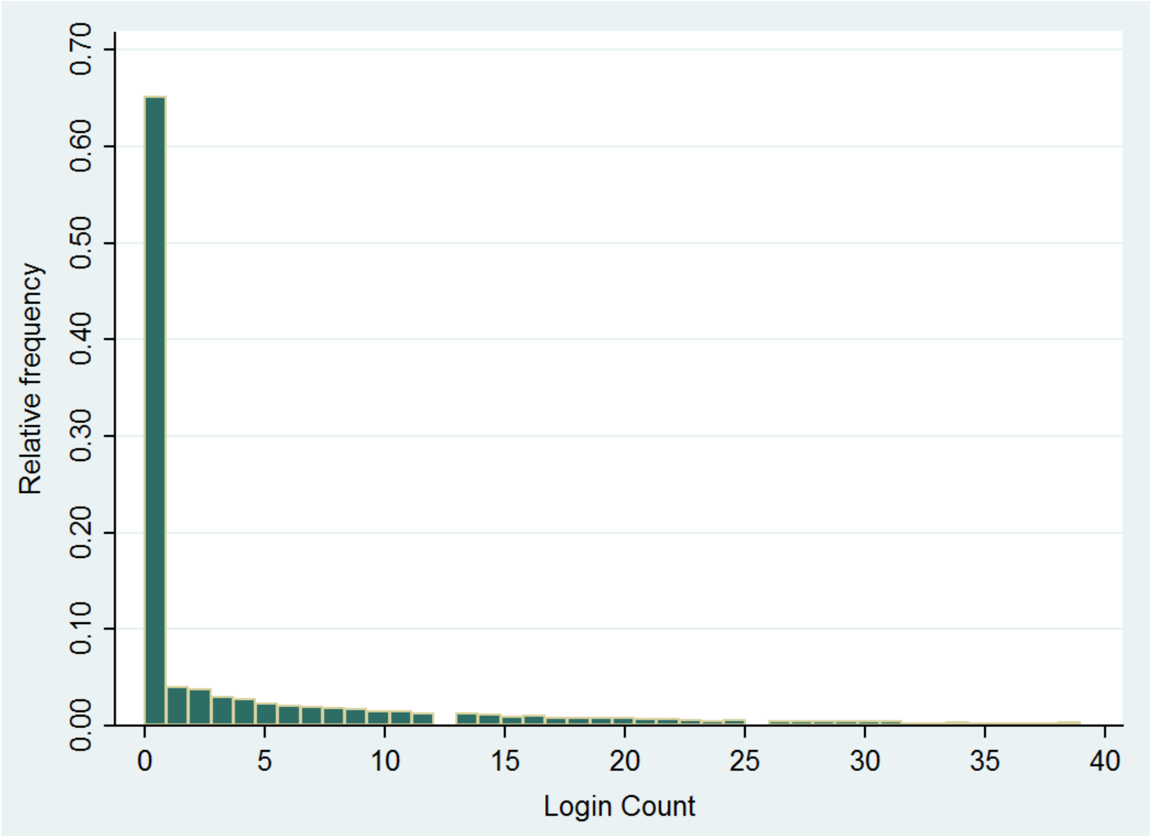

Figure 13. Relative frequency histogram of Login Count for Login Counts <= 40.

This omits the top 4.1% of the distribution. To note, of the 20,000 users with valid profiles, 57.94% have 0 as Login Count. The distribution is positively skewed with an extremely long right tail, 95.9% have fewer than 40 Logins and 0.61% has 100 or more Logins.

Regression Analyses of User Demographic Data

Stepwise regression was chosen to regress the multitude of variables in the large and complex dataset comprising the population data files to remove the more weakly correlated variables and make a best effort for explaining the distribution(s). Stepwise regression, according to the evidence, has a number of flaws as a tool of predictive analysis, (Altman & Andersen, 1989;Derksen & Keselman, 1992). These shortcomings include not always being able to stop with the model with the highest

R^2 value possible for a specified number of predictors; the method may also yield confidence intervals for effects and predicted values that are falsely narrow; it has problems when collinearity is present and when estimating the degrees of freedom, the number of the candidate independent variables from the best fit selected is smaller than the total number of final model variables, causing the fit to appear better than it is when adjusting the R^2 value for the number of degrees of freedom. Despite these flaws, backwards-stepwise regression is used in several sections in the analysis of the study to generate basic descriptive summaries for the large amount of data in this sample.[3]

For the analysis of the Demographics file, a backwards stepwise regression of login count was performed on indicator variables for country (128 different countries), gender, default activity (66 different activities), and whether the user has a Flickr account, Facebook account, YouTube channel, and Twitter account in addition to the continuous variable Age as of 1/1/2014.[4] To facilitate comparisons, the two continuous variables, Login Count and Age, were standardized to have mean 0 and variance 1. Given this standardization, regression coefficients for indicator variables indicate the number of standard deviations of difference between the group included in the intercept and the variables listed separately, whereas the coefficient on standardized Age indicates the number of standard deviations of increase in Login Count for each standard deviation of increase in Age. Additionally, countries and

[3] The Backwards Stepwise Regression approach used here starts with all variables in the regression equations and then removes variables successively, starting with the variable with the largest p value. After each removal of a single variable, the regression equation is re-estimated, and the variable with the highest p value is removed.

[4] The table also uses the robust variance estimator developed by White (1980), which provides consistent estimates of the variances of groups even when the variance is not constant across alll groups.

activities with only one participant were excluded from the analysis as well as observations with missing values of any of the included variables, leaving a sample size of 17,761. Login Count is of particular interest as it is the one reasonable measure inherent in the system that indicates frequency of use of the system proper and the social media account activation is a necessary variable for identifying online sociability factors that are of importance to the study.

Table E3 presents the stepwise regression results, with the countries that are included in the intercept and the activities that are included in the intercept listed below the table. Observe that in an OLS regression, subtracting off the mean of the dependent variable would force the intercept to be equal to zero, but does not force a zero intercept in a stepwise regression. Instead, the estimated intercept is -0.231 ($SE = 0.017$, $p < 0.001$) standard deviations of Login Count below the grand mean, and the countries and activities that have that as their mean are listed beneath the table. Note that the geographic variable of Country was not included as part of the parcel of research questions and is provided only as matter of completion rather than a point of additional investigation.

Each additional standard deviation increase in age, about 10 years, adds 0.02 standard deviations in Login Count ($SE = 0.007$, $p = 0.005$). *On average males login 0.135 standard deviations of Login Count more than females* ($SE = 0.017$, $p < 0.001$). Among social media users, although only 114 users in the estimation sample have Flickr accounts, users with Flickr accounts login on average 1.507 standard deviations higher than users without Flickr accounts ($SE = 0.329$, $p < 0.001$). *Users who hold YouTube accounts are an average of 0.211 standard deviations of Login Count above users who do not have these accounts* ($SE = 0.083$, $p = 0.001$), but users with Twitter accounts do not have logins significantly different than the intercept.

Although Table E3 provides estimates of how much the average number of logins differs by country and activity, these should be interpreted with some caution. Stepwise regression is known to produce estimates that do not converge to population parameters as the sample size grows because it uses outliers in a particular sample that will not appear in other samples. For example, the distribution of Login Count has about 3.7% of its observations greater than two standard deviations from the mean, which is not dramatically different than the 2.3% of observations that would be greater than two standard deviations above the mean for a normal distribution. However, if a user in the right tail of the distribution of Login Count is also one of very few users from a particular country or very few users who pursue a particular activity, stepwise will highlight that country or activity as significantly different. For example, being a person from Angola appears to add 1.514 standard deviations of Login Count above the intercept and appears to add 34 to the average Login Count. However, in our sample, there are only 2 users from Angola and they happen to be in the right tail of the Login Count distribution, and one should not assume that new users from Angola share this characteristic. Because averages by either country or activity are often for small sample sizes, they should be understood as being descriptive of this sample rather than as inferential about habits in those countries.

A scatterplot of the relationship between age and login count is shown in Figure 14. The modest increase in logins with years is evidently driven by observations that are below the mean age of 39, and it appears that an Age R squared term would have aided the fit, as average logins appear to decrease with age after the age of 40.

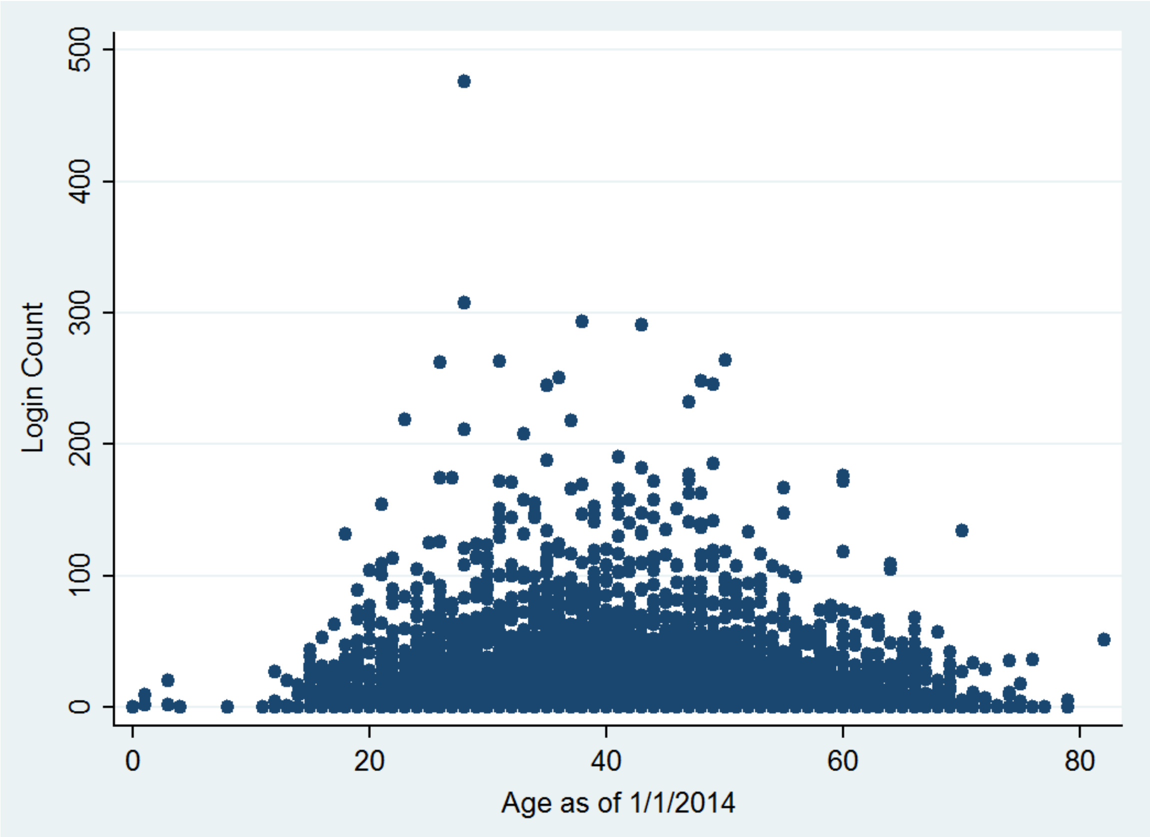

Figure 14. Scatterplot of the relationship between Age and Login Count

The R squared value generated from a stepwise regression is also known to be an upwardly biased estimate of the explanatory power of these variables. Even given this upward bias, the R square for the regression on all of these variables is only 0.04, implying that 96% of the variation in the sample is unaccounted for by country, default activity and the social media variables that have been included. Casual empiricism suggests that there is substantial variation within the categories defined by these indicator variables, such as males as a group, or people from the same country taken as a group. Subsequently, the countries and activities data from the demographics data file were omitted from the regression. This exclusion implies that the amount that these variables add to the mean does not differ significantly from zero. To predict a person's Login Count, if they are in one of those countries or have those default activities, one uses only the intercept, their age, whether they are male and have any of the social media accounts listed in the table of coefficients. For example, for a female user from the US who has canoeing as their default activity and does not have a Flicker account or a YouTube channel, their standardized value for Login Count is given by the intercept, -0.231, plus 0.020 times their standardized age. A female similar in all respects except that her default activity is trail running rather than canoeing would have an average of standardized Login Count that adds 0.133 to the first female's mean because the activity trail running adds 0.133 to the mean.

RQ2

What are the main demographic and anthropometric characteristics of the cohort as recorded by the activity tracking system?

Anthropometrics analysis

The source data file used captures measures of basic physical properties and fitness. Table AC2 in Appendix C lists the user anthropometric variables and how each was measured, while Table AC3 lists the coding for the Suunto movescount fitness index.

In the system's design, the user can alter the values for these variables at any time e.g. BMI which is entered manually rather than imported from a dedicated Bluetooth device or similar. As a result, the data file contains multiple data observations per user. Organising appropriate descriptive analysis required computation of the mean, median, maximum and minimum values for each variable taken across the sum of the user's records. The averages and standard deviations for the same are presented in the analyses for this data source file. Each user has many observations in the anthropometrics file. Averages over all these observations would represent the users by their frequencies in the sample. For this reason, summary statistics for the observations on any user are stored in the collapsed anthropometrics file prepared by a specific STATA script file. Each user in the anthropometrics file has one record in the collapsed anthropometrics file generated by the script file and that in effect has the number of observations they have in the Anthropometrics file and the mean, median, max and min for each variable taken across the user's records. Averages and standard deviations of these variables are used throughout the analyses in this section. Thus the average of the average BMI, is the average of each user's average BMI, for example. Table E4 reports summary statistics for these variables, and Figures 15, 16 and 17 provide error bar plots for the BMI, Fitness Index, and Resting Heart Rate variables respectively.

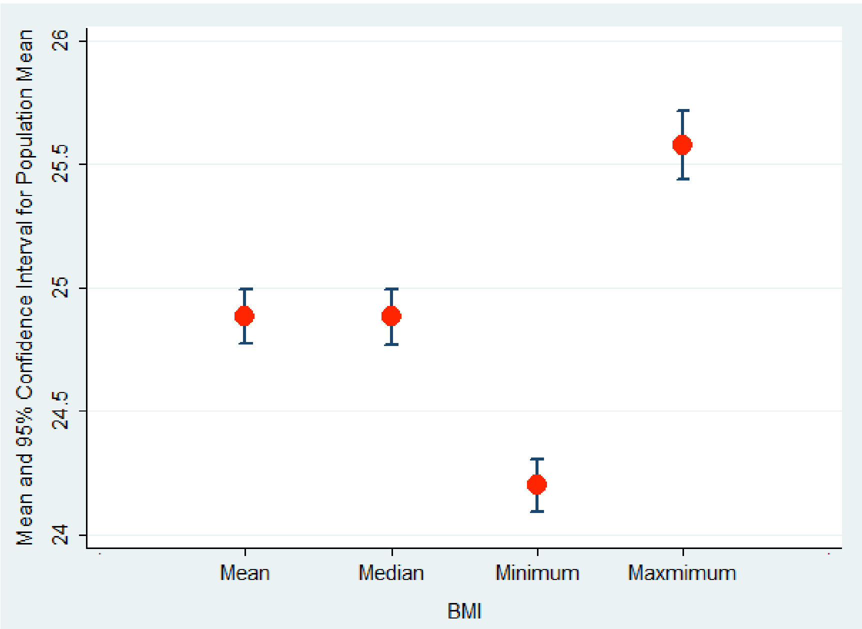

Figure 10. Boxplot of the distribution of BMI values

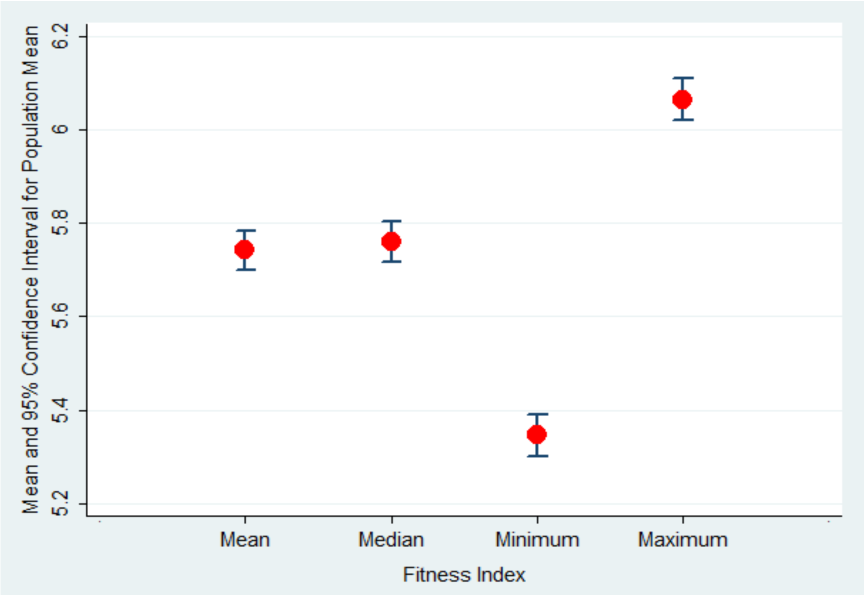

Figure 16. Boxplot of the distribution of Fitness Index values

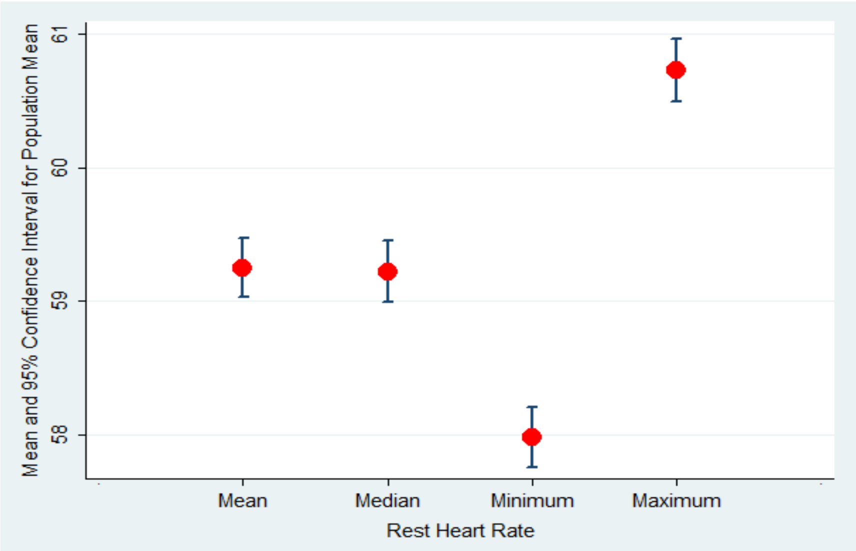

Figure 17. Boxplot of the distribution of Resting Heart Rate (bpm) values

Regression Analyses of User Anthropometric Data

Table E5 provides a correlation matrix between age and the anthropometric data. There are consistently strong correlations between the anthropometric and "fitness" measures. For example, if the users have an above average BMI, then they probably also have an above average weight and are also, relative to their peers in this data set, could be considered out of shape by the other measures. Also, if they have an above average BMI then probably their max of BMI and their min of BMI are above the average of the min BMI and the average of the max BMI. The positive correlations among these mean that if they're fit (or not fit) by one of these measures, then they will tend to be fit (or not fit) by the others as well – as indicated by the large correlations. It seems odd to have Fitness Index Mean and Fitness Index Median enter the some equation with opposite signs, the explanation may be that there must be some people for whom these two measures are not all that correlated. Some of the significance evident in this table can also be attributed to the large sample size

A subsequent stepwise regression of Login Count on all anthropometrics variables including maximum and minimum values removes Weight Max, BMI-Min, BMI-Max, and BMI-Median, Rest-HR-Mean and Median, FitnessIndex-Max, Weight-Min and Weight-Median from the model at p => 0.1000 as revealed in Table E6.

Login counts are regressed on the mean values of the anthropometric measures, Weight, BMI, Resting HR, and Fitness Index with results presented in Table E7. For example, each 1-point decrease in BMI, Logins increase by 0.901. The regression has an R^2 of only 0.043, so there remains a great deal of unexplained variation in logins.

RQ3

What level and type of online social interactions have occurred by and between individual members of the user population using the systems online social network?

Followers and Following Relationships Analyses

The Followers data file comprises a set of variables that represent the list of users in the system and those other users they are following in the system and which of these users are following them. It is assumed that these following relationships constitute an overt expression of interest by one user toward another. It is not known if these users are known to each other offline prior to establishing any following relationships online in this system. This assumption aligns with the intended system function as designed by the vendor, which is to encourage online sociability. The relationship possibilities are such that a user may follow nobody at all and be followed by no other users. A user may also follow one or more users and be followed by one or more users. The descriptive statistics for the number of people a user is followed by has a mean of 1.71 and a standard deviation of 7.4, indicate an average of 1.712 for a sample of 4,745 people and a standard deviation of 7.449 and a maximum of 476. Figure 18 shows the distribution of means for the Follows-Following relationship types at the corresponding 95% Confidence Intervals.

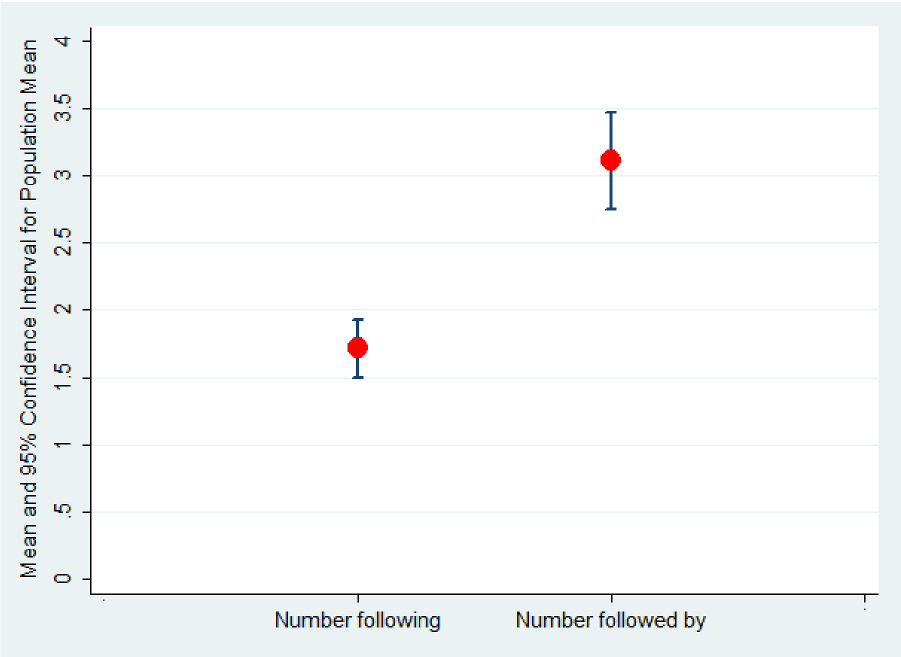

Figure 18. Distribution of sample mean and 95% confidence intervals for Population Mean, Number of People a User Follows and Number of People Following a User.

Figure 19 shows the relative frequency distribution of the Number of People Following for IDs that have 7 or fewer followers, a group that accounts for 98.4% of the sample. The sample is highly skewed, with a right tail that extends to a maximum of 476 followers, has another observation with 101 followers, and has 18 more users with between 20 and 80 followers. It is probable that the outliers represent the following activity for well-known athletes in a particular Activity Name but due to anonymity constraints this cannot be proven. The 90th, 95th, and 99th percentiles of the number of users following a particular user are given by the numbers 2, 4, and 11, respectively. If we eliminate the users above the 99th percentile from the sample, then the remaining sample of 4,703 people have a mean of 1.383 followers with a standard deviation of 1.058 followers.

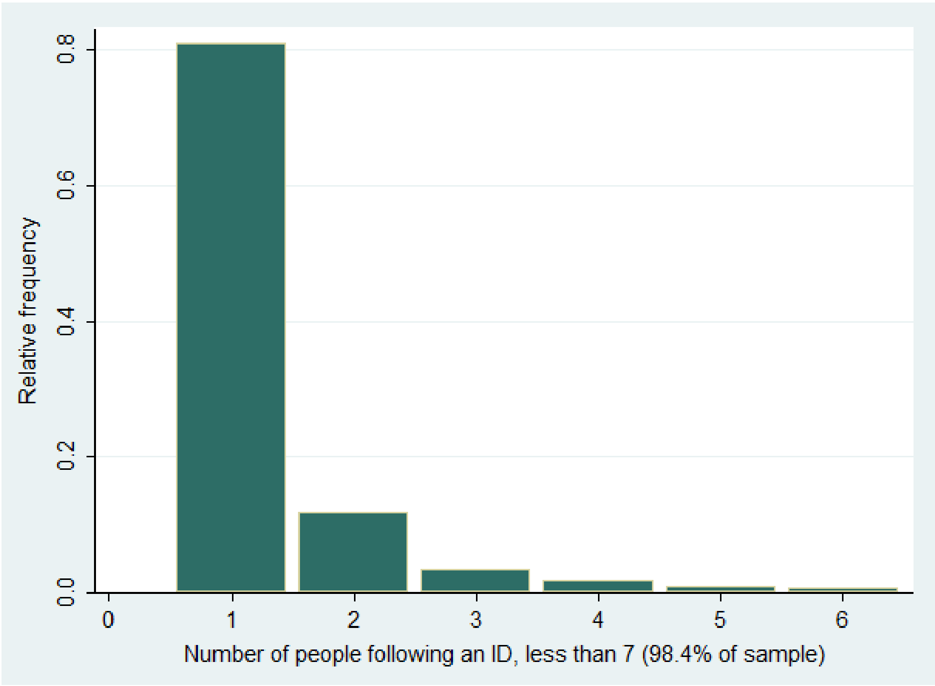

Figure 19. A relative frequency distribution of the Number of People Following Another User ID

The mean number of people a user follows is 3.11 with a standard deviation of 9.362 for a sample size of 2,411. Figure 20 shows these means along with the 95% confidence interval for the population mean, [2.752, 3.470]. Once again, the data has a long right tail, with the median being 1 person followed, the 75th percentile being 3 people followed, the 95th percentile being 9 people followed and a maximum of 346 people followed.

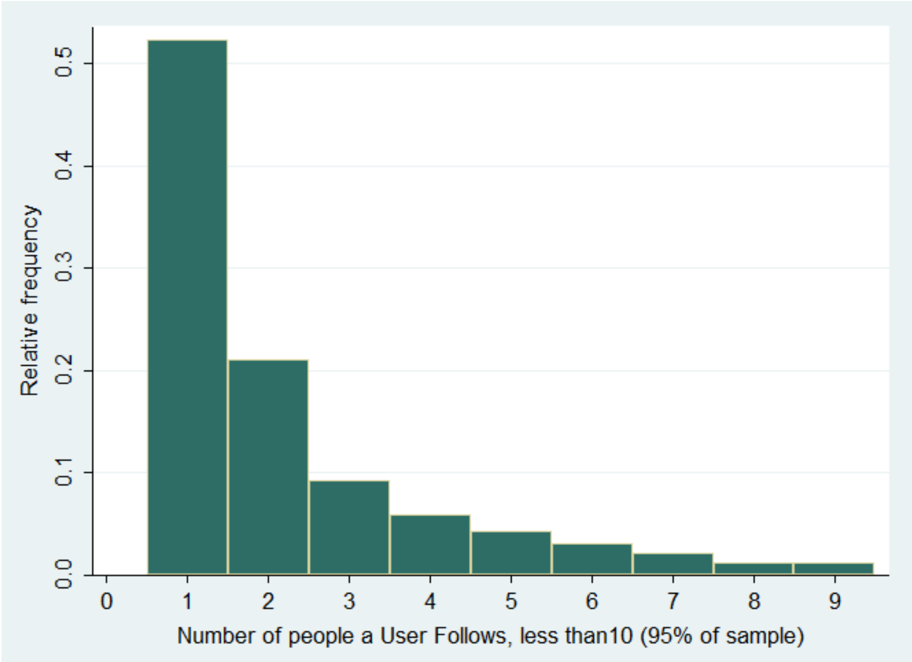

Figure 20. Relative distribution of the Number of Users Followed by a User ID, for Users Following 9 or Less Other User

Regression Analyses of Follows-Following Relationship Data

As the focus of the study is to understand system usage patterns for the digital exercise tracking system, the identification of relationships between variables of the data set and the number of times a user logs into the system, known as Login Count, is particularly important. It is to their online social ties within the system itself that attention is drawn as they may assist in deriving a better understanding of any associations between social interactions and exercise session uploading and online system usage behaviours.

Figure 21 shows a scatterplot of Login Count by the Number of People Following a User- ID. Observe that for reasons of confidentiality, the Demographics file that contains Login Count omits some of the users that are the outliers in the

Number of People Following a User-ID and also fails to match for a large number of additional observations, so that the sample size for the regression is restricted to 874.

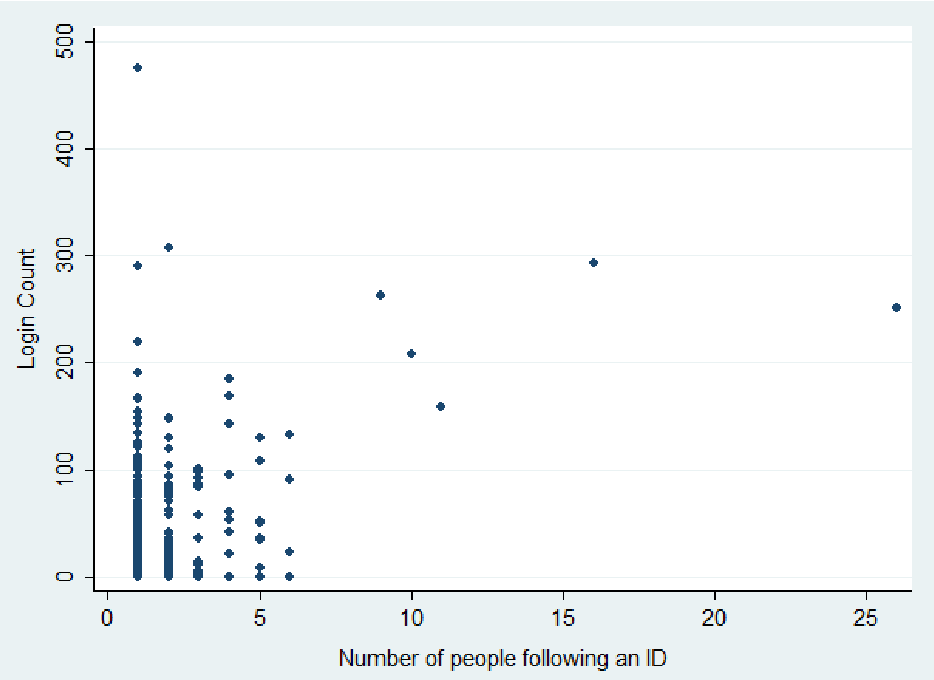

Figure 21. A scatterplot for regression of the Number of People Following a User ID on Login Count

A correlation analysis of the association between Login Count and the Number of People Following a User ID shows an r = 0.378 ($p < .001$), indicating a modest positive linear relationship between these variables is shown in Table E8.

The regression model shown in Table E8 indicates that the Login Count for a user increases by an average of 11.436 (*SE* = 0.949, $p < 0.001$) for each additional follower. This regression model is somewhat sensitive to the remaining outliers in the data. Restricting the sample to different numbers of followers corresponding to the 99th percentile of followers, 11 or fewer followers, or the 95th percentile of followers, 4 or fewer followers, produces the results provided in the second and third columns of Table 15. A statistically significant relationship between number of followers and Login Count obtains in each subsample, but the values of R^2 decline, indicating less and less variation in the sample explained by the number of followers.

Figure 22 shows a histogram of the Number of Moves made by a User by the Number of People Following the User. The graph uses the "jitter" function to randomly disperse points (within a circle) that would otherwise appear as a single point As shown in Table E9, for the full sample of 471 users who can be matched from the Exercise Sessions file and the Followers file, the estimated slope suggests that the number of moves made by a user increases by 4.728 with each additional follower. Again regression coefficients are somewhat sensitive to the inclusion of outliers, with estimated slopes changing from 4.728 to 5.460, 6.326, 5.823, 5.097, and 4.397 as the five outliers with the largest effects are removed. Restricting the sample to include only users with six or fewer followers generates an estimated slope of 5.393. R squares range from 0.186 to 0.010 for these models, with the smallest R square being for the model with less than or equal to six followers.

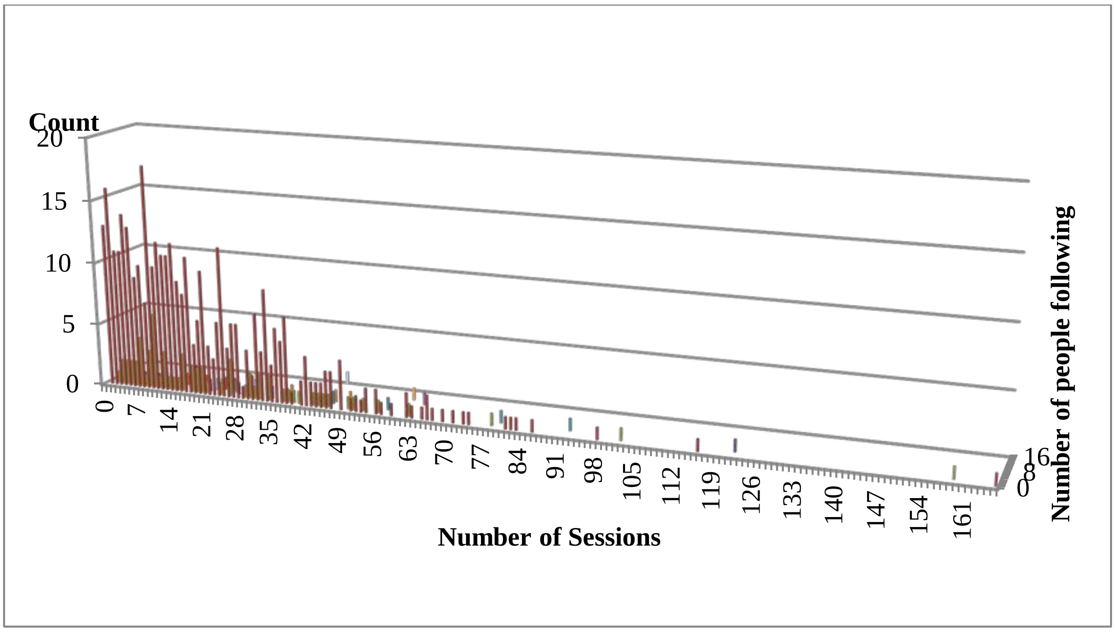

Figure 22. A Histogram of the Number of Moves by the Number of People Following a User

A correlation analysis of the association between the Number of Moves and the Number of People Following a User shows an r = 0.144 (p = 0.002) indicating a weak positive linear relationship between these variables. If we invert the view of social relationships in the system based on following behaviour and assess the associations between Login Count, Moves and the Number of People an individual follows, a rounded view results. The histogram of Login Count by Number of People a User Follows has a sample size of 2,611 and is shown in Figure 22.

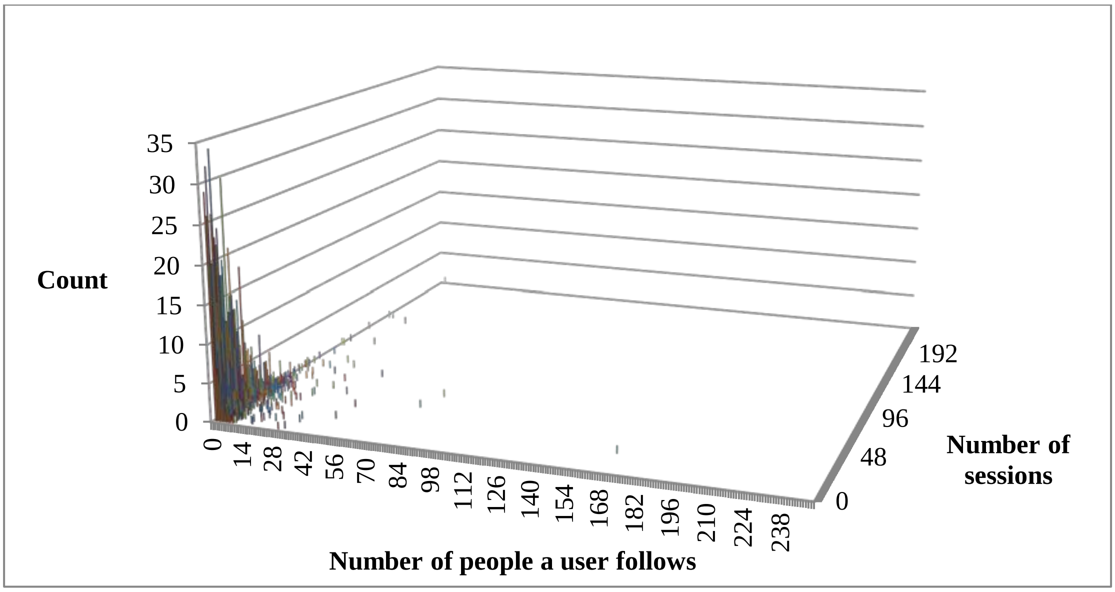

Figure 23. A histogram of Login Count by Number of People a User Follows n=2611

A subsequent correlation analysis found a modest positive linear correlation between Login Count and the Number of People a User Follows, with $r = 0.274$ ($p < 0.001$).

A simple linear regression slope estimate as shown in the first column of Table E10 implies that *each additional person a user follows is associated with 0.938 additional logins* ($SE = 0.065$, $p < 0.001$), *on average*. To explore how this is affected by the long right tail of the number of people a user follows, the three remaining columns consider samples restricted to the 99th percentile, 95th percentile and 90th percentile of number of users a user follows (less than or equal to 22 people followed, 9 people followed and 6 people followed, respectively). For samples with from 6 to 22 people followed, the number of Login Counts increases by 2.2 to 2.6 for each additional user followed. All of the estimated coefficients are statistically significant, but the amount of explained variation decreases from 0.074 to 0.013 as the sample size decreases with fewer people being followed.

The system allows for users to login to simply browse the system, adjust settings, plan Moves and read content and or to upload completed exercise sessions (moves) and interact online with others within the system and optionally publish Move data to external social media services. This drives an examination of the associations between the number of users a user follows and the uploaded moves of the user. Figure 24 depicts the scatterplot of the Number of Moves by a User by the Number of People the User Follows for the sample of 1,309 users who can be matched from the Followers file and the Exercise Sessions (moves) file.

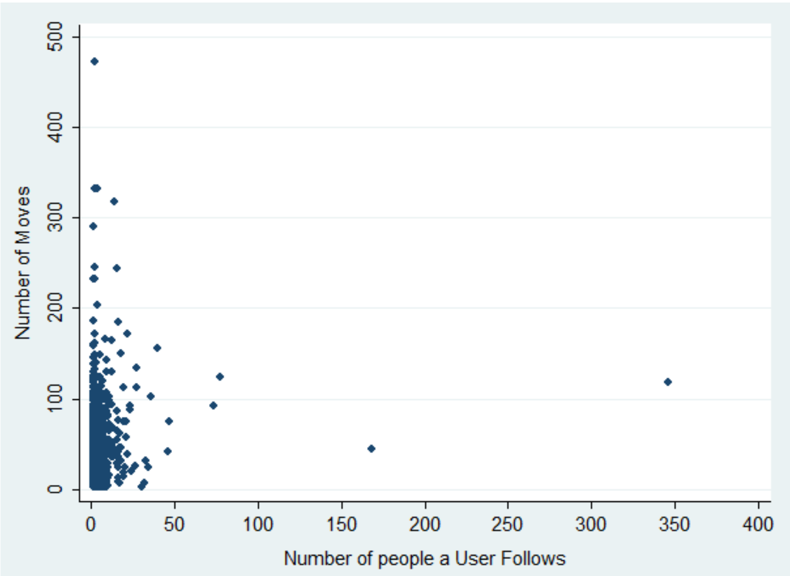

Figure 24. A scatterplot showing the Number of Moves by Number of People a User Follows, n=1,309

A subsequent correlation analysis found a weak positive correlation between the Number of People a User Follows and their own Number of Moves of r = 0.132 (p < 0.001). The regression model for the mean Number of Moves as a linear function of the Number of People a User Follows in Table E11 reveals a slope of 0.220 (SE = 0.046, p < 0.001), *implying the average number of moves for a user* *increases by 0.22 for each additional person a user follows*. The R^2 of 0.018 suggests that almost all of the variation in number of moves remains unexplained. To investigate the effects of large numbers of people followed by a user, the table also shows regression coefficients for samples that include the 99^{th}, 95^{th} and 90^{th} percentiles of the number of people a user follows, which are 27, 10 and 7 respectively. As the right tail of the distribution of the number of people a user follows is omitted, the regression slope coefficient increases by a factor of slightly more than 5. However, the values of R^2 are all less than 0.05, so that none of these models explains much variation in number of moves.

The bivariate regression models completed here that examine the activity of users following each other in general and the circumstance of uploaded exercise moves reveal relationships between the Average Number of Login Counts or Moves and the Number of People a User is Followed By or Follows. At first glance, all of these models predict dependent variables better than just using the sample means alone. However, any accurate and meaningful predictions using the model have to be caveated by the underlying very large variance in the data. As a result, the sample mean predicts poorly in these samples. For example, for the file that merges Login Counts with Number of Followers, the mean of Login Count rounds to 21 but slightly more than 70% of the sample has 20 or fewer logins and the modal observation is 0 logins, which is obtained for 407 (47%) of the 874 users in the merged source. Examined in this light, the regression models clear a very low hurdle by predicting better than the sample mean because the sample mean predicts so poorly because of the extreme skewness and high variance of the data. In short, these regression models will not be particularly accurate and reliable as predictors of the number of Login Counts or Exercise Moves. It is important to note that for each model, logarithmic transformations of the dependent and independent variables were tried with negligible effect on the values of R^2. Interestingly though, the models *do indicate that both the average number of logins and the average number of moves increase with the number of people a user follows or is followed by*.

RQ4

How many users publish their exercise sessions to Twitter, and what characterises these users demographically and anthropometrically?

RQ5

What association if any, exists between a user's anthropometric characteristics and their published moves in this system?

Uploaded Exercise Sessions (Moves) Analyses

In the movescount.com system, when a user completes the recording of a physical activity using the wearable device and uploads the data for this to the movescount web site, it is identified to the system as a *move*. In managing the data output for the source population the collection of multiple instances of moves is known as an exercise sessions file. Table 8 summarizes the scoring of the Training Effect (TE) scale.

Table 8. Suunto movescount Training Effect (TE) scale

TE score	Suunto description
1 minor training effect	Improves recuperation and doesn't advance aerobic endurance.
2 maintain training effect	Maintains aerobic endurance and allows for better cardio-vascular function and more intense training in the future.
3 improving training effect	This improves aerobic condition if performed 2 to 4 times per week. Training at this level does not require special conditions for recovery.
4 highly improving training effect	If repeated 1 to 2 times per week will highly improve aerobic condition. For optimal t requires 2 to 3 recovery workouts (TE 1 to 2) per week.
5 over-reaching training effect	This has a major effect on boosting aerobic condition but requires a sufficient recovery.

Descriptive Statistics for Uploaded Moves

The descriptive analysis process focused on the primary exercise intensity and value outcomes of Training Effect (which we have established incorporates user-move heart rate data), Calories and Feelings, with the descriptive results displayed in Table E12. The TE scale ranged from zero to 5 with a mean of 3.04 (*SD* = 1.132). Feelings ranged from one to five with a mean of 3.573 (*SD* = .953). The calories variable ranged from zero to 14,046 with a mean of 606.556 (*SD* = 470.074).

Boxplots for these variables in Figures 25 and 26 provide additional detail on the distributions of these variables.[5] With the distributions for TE and Feeling, only 365 of the 16,854 (2%) uploads of feelings ratings are "Poor," and these represent outliers of the voluntary uploads for Feeling.

[5] The whiskers in this boxplot have "caps" at p75 + 1.5 x (p75 – p25) for the upper cap and p25 - 1.5 x (p75 – p25) for the lower cap if the data extend to this range, and the whiskers terminate at the maximum and minimum if the data do not extend to the cap locations. Outliers are denoted by dots outside the caps of the whiskers.

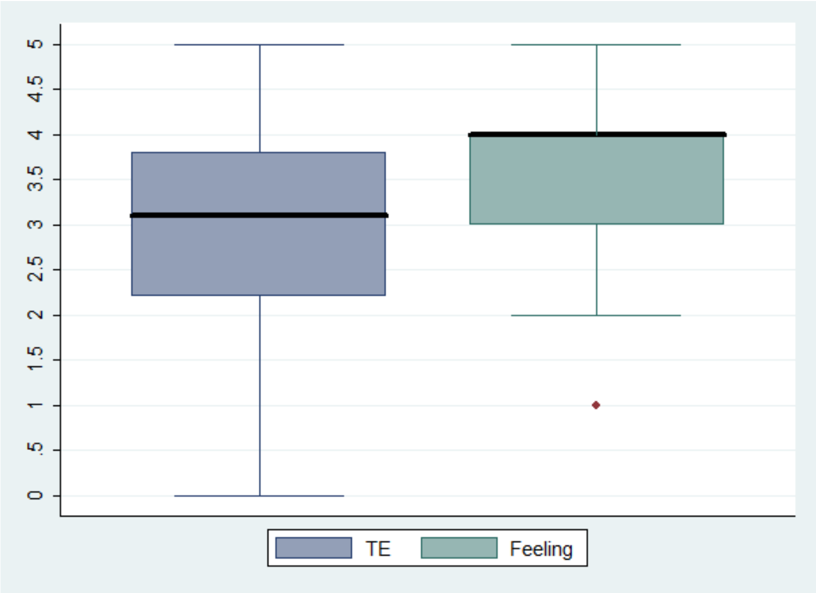

Figure 25. A boxplot of TE and Feelings distribution and outliers.

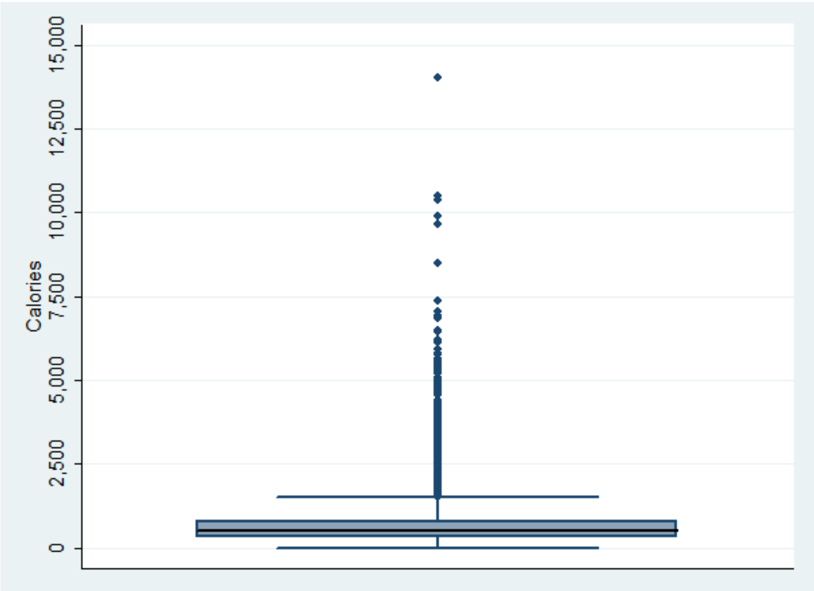

Figure 27. A boxplot of Calories Expended in Moves

For Calories, in the boxplot shown as Figure 27, there are a large number of outliers above the whisker at 1524.5. It is proposed that these likely represent ultra-endurance activities performed over extended periods of time. For example, there are three sessions that burn more than 10,000 calories, one is a *trekking* activity that lasts

32 hours, another is a *running* activity that lasts 23.5 hours and the other is a not specified activity that lasts 16.6 hours. Anecdotally, discussions with the vendor appeared to point to a skewed representation of ultra endurance runners in its market of users of the device although there are only 3 observations in 120,000 with more than 10,000 calories burned which are most likely to be ultra-endurance event-generated moves for these individuals.

Regression Analyses for Uploaded Moves

A correlation analysis of the association between each of the variables in the Moves data file is detailed in Table E13. It is important to understand the data management process undertaken to enable this and the regression analyses to be done. Firstly, note that we have one observation of a Login Count instance for each user, but moves are available by activity and many users perform more than one activity. To create a data analysis file from the source files for this table, we started with a file that has a single record for each move by a user with their total Login Count attached to each record and then divide the user's Login Count in each of these records by their total number of moves. This file is then collapsed to a file that has a single record for each combination of a user and activity that the user has at least one move for. For each activity, the variable Login Count by Activity is the sum of the variable Login Count divided by total moves by a user, and therefore allocates a user's Login Count across the activities they perform. The variables Calories, TE, and HrAvg are averages by user and activity. The total number of observations is the sum of the number of users who both perform each different activity in the Exercise Sessions (moves) validated source data file and have a Login Count from the demographics validated source data file.

Correlations between the three metrics of workout intensity denoted as Training Effect (TE), exercise average heart rate (HrAvg), and Calories range from a moderate correlation of 0.366 ($p < 0.001$) between HrAvg and Calories to a very strong correlation 0.807 ($p < 0.001$) between TE and HrAvg, with the correlation between Calories and TE of 0.506 falling between these two extremes. Given the sample sizes, all of these correlations are statistically significant at conventional levels. The measures Number of Moves and Login Count have a moderately strong correlation of 0.44, which is also statistically significant ($p < 0.001$). The correlations between system use indicators, Login Count and Number of Moves, with the metrics of exercise intensity show only weak positive correlations. It is apparently *not the case that the count of Logins or Number of Moves is associated with exercise intensity variables to any large extent*.

To further explore the relationship between Number of Moves and what is termed exercise intensity-outcomes variables of TE, HrAvg and Calories, a stepwise regression of Number of Moves on these variables was estimated and all of the variables were retained. The sample size is 5,875 users. The F statistic for the regression model has a value of 96.17, which with 2 and 5,872 degrees of freedom implies that the model is statistically significantly better than prediction using the mean number of moves at $p < 0.0001$ level of significance. However, the R square for the model is only 0.0317, suggesting that there is a large amount of variation left to be explained. Estimated coefficients for variables that are significant to less than the 0.10 level of significance are presented in Table E14.

The F statistic for the model used as the basis for Table E14 has a p value < 0.0001, suggesting that the model predicts better than the sample mean, but once again, the R square is only 0.01. If the same model is estimated after removing the large number of outliers in Number of Moves, the estimated coefficient for TE drops to 2.38.[6] TE is also associated with a decrease in Login Count, with every 1-point increase in TE implying -3.9 (SE = 0.637, $p < 0.001$) additional logins. This may be consistent with the TE index and interpretations i.e. the more intense an exercise session and the greater its TE, the less of such sessions should be completed over the period of a week and the greater the rest or recovery needed. By contrast, both HrAvg and Calories are positively correlated with Login Count. A 10 beat per minute increase in HrAvg implies 1.7 additional logins ($p < 0.001$) and a 100-calorie increase in workout intensity implies 0.6 additional Logins ($p < 0.001$).

Table E15 displays regression coefficients when the use of social media to publish *moves*, specifically, Twitter, is included with the variables. A user's decision to publish a *particular* move to Twitter may be dominated by variables idiosyncratic variables we do not observe such as their current opportunity cost of time, whereas whether they ever publish a move To Twitter is more indicative of their willingness/ability to use social media. Therefore Publish to Twitter is a binary variable with the value 1 if a user ever publishes their *move* to Twitter and 0 otherwise. significantly better than simply using the sample mean and again has an R square of 0.03. *The estimated coefficient on Publish to Twitter suggests that users of Twitter have 5.1 moves more* (SE = 1.435, $p < 0.001$) *than users who do not Publish to Twitter*.

Continuing with the investigation of the strong finding that publishing moves to social media has a strong association with the total number of moves completed and uploaded to the system, the following regression reveals that the online social

[6] The third quartile is 20 moves and the interquartile range, (p75 – p25), is 15, so that an outlier is defined as a person who has more than 42 moves.

behaviour of Publish to Twitter is positively correlated with Login Count. Users who Publish to Twitter have an average of 13.2 more logins (*SE* = 2.857, $p < 0.001$) than people who do not Publish to Twitter. Table E16 displays estimated coefficients for a model that includes the Publish to Twitter binary variable. The model F statistic has a p value < 0.0001, but again the R square is only 0.02.

RQ3

What level and type of online social interactions have occurred by and between individual members of the user population using the systems online social network?

Data Analyses of THUMBS

The data file used for the analyses in this section contains the records of users who have indicated a *thumb* (a thumbs up icon flagged by the system as being either on or off as determined by a user mouse-click which is deemed as a positive affirmation by one user toward another for the completion of a *move* in the system) for a *move* uploaded by themselves or other users. It is intended as a "*likes"* equivalent of the commonly used affirmation of posted content behaviours in large public online social networks such as Facebook. Table C6 in Appendix C describes the variables in the file.

Table E17 presents descriptive statistics for the thumbs data. In the Thumbs file, there are 7,219 instances in which a user used the ability to send thumbs up to him/herself or others. A total of 2,848 users received thumbs and 3,034 users sent thumbs. The majority of the thumbs sent, 4,880 (67.4%) were "self-appreciation", or thumbs that a user sent to their own record. Table E17 provides descriptive statistics for thumbs received by users and thumbs sent by users, respectively.

On average, users receive 2.5 thumbs, and on average 72% of thumbs indicate self-appreciation or self-affirmation. More than 75 percent of users received two thumbs or fewer and only receive thumbs from themselves. The data for thumbs sent reflect the same phenomenon, as more than 75 percent of users send 2 or fewer thumbs and only send thumbs to themselves.

Figures 28 and 29 are frequency histograms of the number of Thumbs received and sent and indicate the extreme skewness of these distributions. For example, for Thumbs Received 98.1 percent of users receive no more than 12 thumbs total and 99 percent receive 20 or fewer thumbs total. In addition to the maximum number received, 274, there is one observation at 112, and a total of four observations with more than 50 received. It may be that the outlier values for a small set of users can be attributed to their popularity as recognised elite athletes. However, with no ability to correlate user identity number with real world user identity because of anonymity constraints this reasoning is only conjecture at this stage.

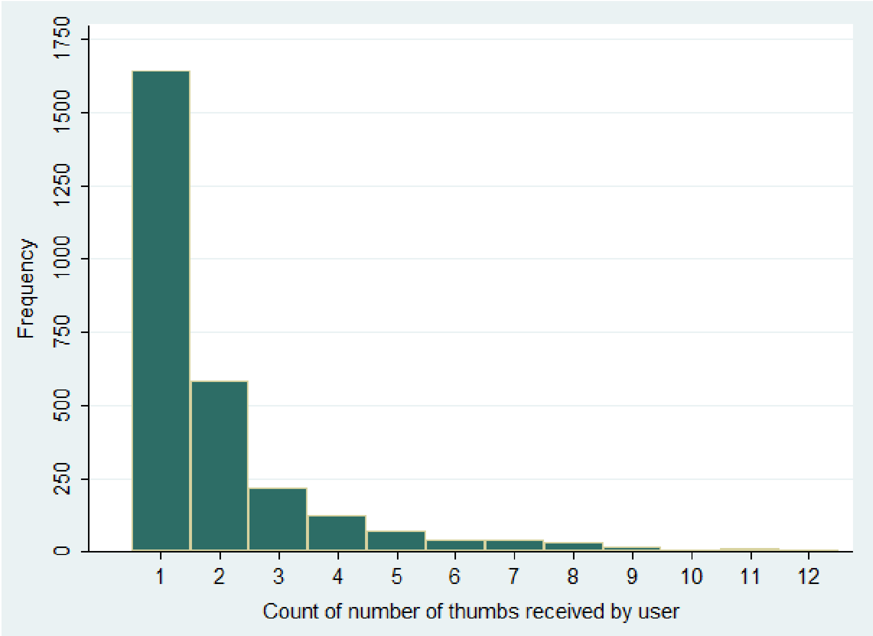

Figure 28. Histogram of Number of Thumbs Received when this Number <=12

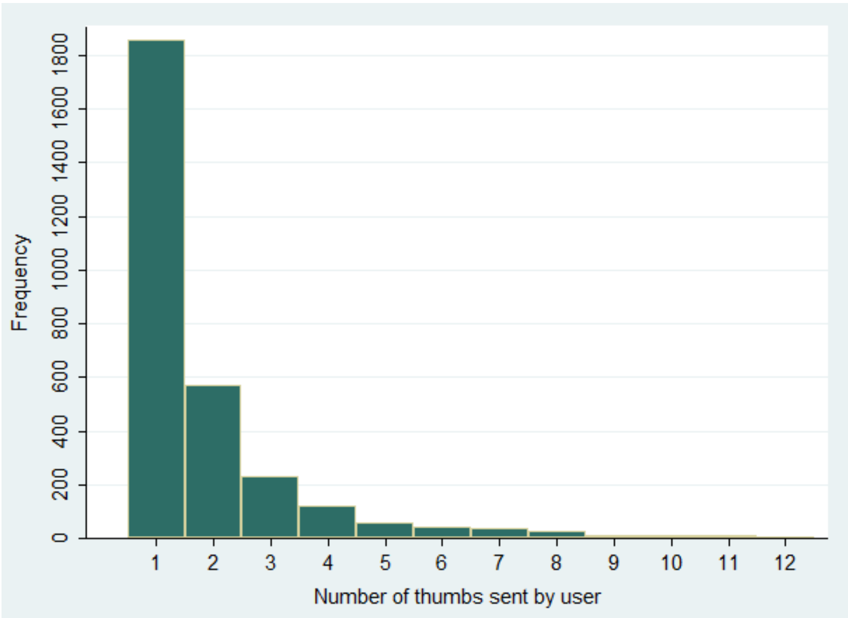

Figure 11. Histogram of Number of Thumbs Sent when this Number <=12

As shown in Figure 29, for Thumbs Sent, the 99th percentile is 17 thumbs sent, but there is one observation at 250, one at 221 and a total of three greater than 50.

Regression Analyses for THUMBS

Driven by the need to better understand what system factors affect the use of thumbs as an interactive behaviour online, a stepwise regression of Number of Thumbs Received on Number of Moves, Login Counts or any of the anthropometric variables or age from the demographics data file was conducted. However, only the value for the Constant is significant at the 0.01 level of significance. There is no association that can be statistically validated to exist between a user's anthropometric attributes, their age, the number of moves they upload to the system or the number of times they log in to use the system and the number of thumbs they receive. The same stepwise regression was tried with the logarithm of thumbs received as a dependent variable with the same outcome. There was a statistically significant relationship between number of shouts received and thumbs, but the coefficient is 0.01 which is awfully small.

RQ3

What level and type of online social interactions have occurred by and between individual members of the user population using the systems online social network?

Data Analysis of General Shouts

The data file used for the analyses in this section contains the records of users who have written in narrative, free form text format an entry onto another user's active profile page. These comments are recorded in the system as *shouts*. The data provided does not indicate the tone of these *shouts* i.e. if they are positive or negative. The variables represented in the data file are described in Appendix C**.**

Descriptive statistics for General Shouts

Table E18 provides descriptive statistics for the Number of General Shouts Sent by users and the Number of General Shouts Received by users. A relatively small number of users make an average of 4.5 shouts each to a larger group of receivers who receive an average of 1.9 shouts each. Each of these distributions is extremely positive skewed, as is evidenced by more than half of the users making and receiving only one shout whereas the maximum of shouts made is 832 and the maximum of shouts received is 135.

Figures 30 and 31 are frequency histograms representing the distribution of General Shouts Made and General Shouts Received by the cohort. These figures are truncated at 16 or fewer shouts made and received in order to show detail, but 16 or fewer shouts accounts for more than 98 or more than 99 percent of users for shouts made and received, respectively. In fact, *users with 5 or fewer shouts made/received account for more than 90 percent of all users.*

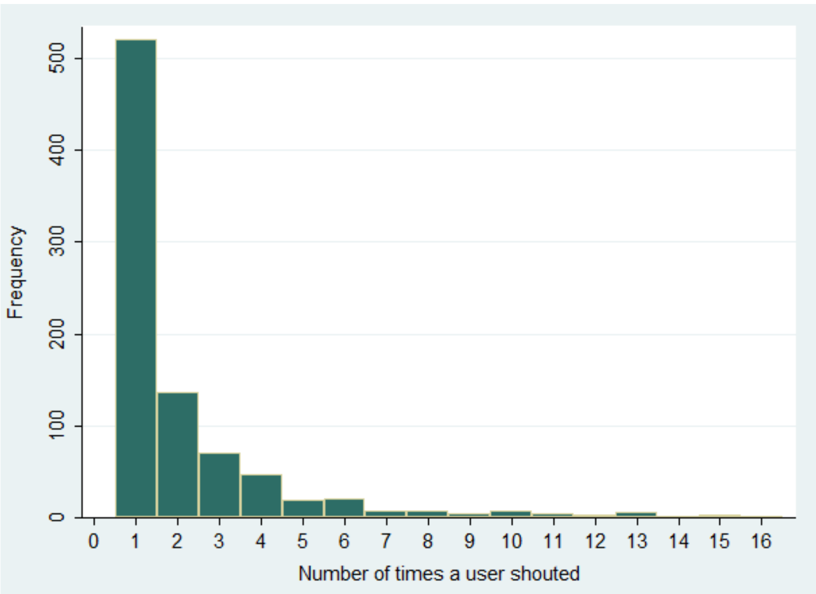

Figure 30 Frequency histogram for Shouts Made, Where Shouts <=16

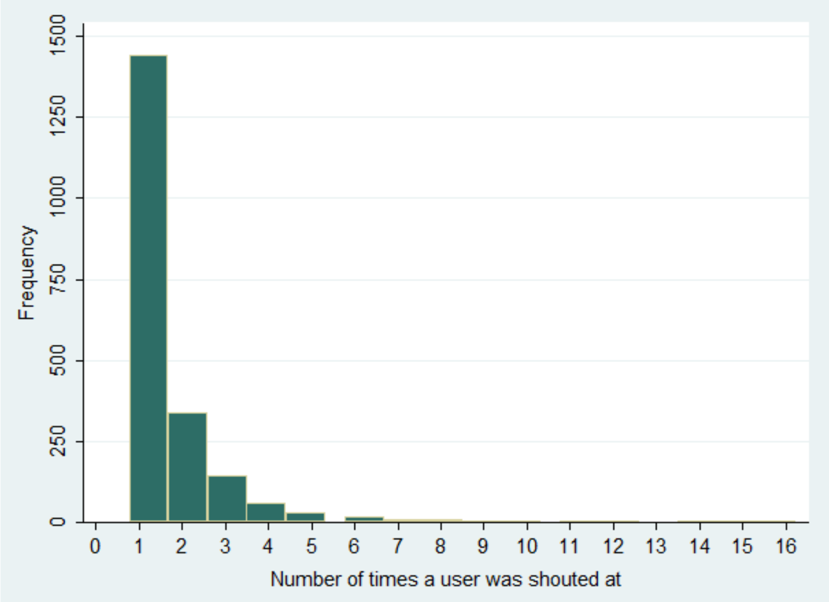

Figure 31. A frequency histogram for Shouts Received <=16

Both the Number of General Shouts Made and the Number of General Shouts Received are moderately positively correlated with Login Count at less than a 0.001 level of significance, although the correlation is only 0.30 for General Shouts Made and 0.39 for General Shouts Received. Neither of these variables is statistically significantly correlated with the number of moves or with any of the anthropometric measures.

Table E19 provides regression coefficients from a stepwise regression of the Number of General Shouts made on Login Count, Age and the anthropometric measures median of BMI Weight, Rest HR and Fitness Index. Consistent with the correlations, **only Login Count is statistically significantly correlated with number of shouts made** and is the only variable displayed in the table**.** The F statistic is 26.20 with 1 and 260 degrees of freedom and a *p*-value of < 0.0001, indicating that the null hypothesis that the regression model does no better at predicting shouts made than the mean of shouts made can be overwhelmingly rejected. The R square for the model is 0.09, which leaves much variation unexplained but is acceptable for a bivariate regression. The estimated coefficient on Login Count, 0.28 ($SE = 0.055$, $p < 0.001$), implies that *on average about one additional shout is made for each four additional logins.* A null hypothesis that the mean number of shouts made is the same for males and females was also tested using a t test, and could not be rejected ($t = 0.171$, 260 df, p-value = 0.864).

Table E20 provides regression coefficients from a stepwise regression of the Number of Shouts Received on Login Count, Age and the anthropometric measures median of BMI Weight, Rest HR and Fitness Index. Again consistent with the correlations among these variables, **only Login Count remains in the regression** and is the only variable displayed in the table . The F statistic is 23.91 with 1 and 133 degrees of freedom and a p-value of < 0.001, indicating that the null hypothesis that the regression model does no better at predicting Shouts Received than the mean of Shouts Received can be overwhelmingly rejected. The R square for the model is 0.15, acceptable for a bivariate regression and the estimated coefficient implies 1 additional shout received for approximately 13 additional logins ($B = 0.076$, $SE = 0.016$, $p < 0.001$). The null hypothesis that the mean number of shouts made is the same for males and females was also tested using a t test, and could not be rejected ($t = 0.090$, 133 df, p-value = 0.928).

RQ3 What level and type of online social interactions have occurred by and between individual members of the user population using the systems online social network?

Data Analyses for Shouts Made at Moves

The data file used for the analyses in this section contains the records of users who have written in narrative, free form text format an entry for another user's *move*. These comments are recorded in the system as *shouts*. The data provided does not indicate the tone of these *shouts* i.e. if they are positive or negative. The variables represented in the data file are described in Appendix C.

Descriptive statistics for Shouts at Moves

There are a total of 5,142 shouts made at users. Table E21 provides descriptive statistics for the Number of Users Receiving Shouts at Moves and the Number of Moves Receiving Shouts. The first column of the table indicates that 1,467 users received shouts, with an average of 3.5 shouts received by user. The second column provides the number of moves receiving shouts, and indicates that 3,913 different moves received shouts with a move receiving 1.3 shouts on average. The last column indicates the number of moves by user that received a shout. Of the 1,467 users that received shouts, each user received shouts during 2.6 moves on average. All of these data are positively skewed.

Figure 32 is a histogram of the Number of Shouts Received by User at Moves for Shouts Received less than or equal to 20, which accounts for 97.3% of all shouts made. The 99th percentile of the distribution is 39 shouts, and in addition the maximum number of shouts received by a user of 111, there were seven users who received more than 50 shouts. Figure 33 is a histogram of the Number of Shouts Received by Move, for moves receiving six or fewer shouts, which accounts for 99 percent of all shouts. The maximum Number of Shouts Received at a Move is 17, and in addition there were 6 moves that received 10 or more shouts.

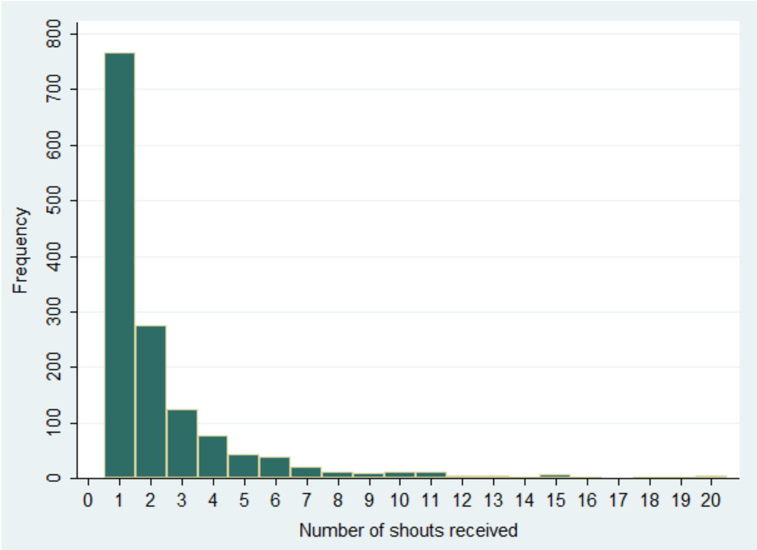

Figure 32. A histogram for the Number of Shouts Received by User for Number of Shouts <=20.

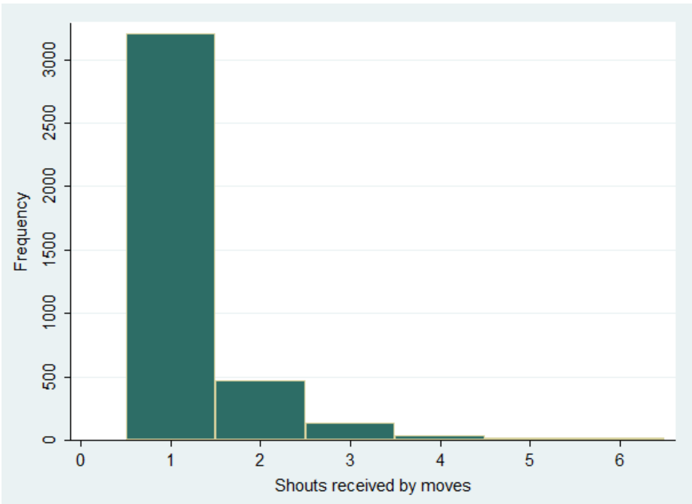

Figure 33. A histogram for the Number of Shouts Received by Move, for Number of Shouts Received ≤ 6.

Regression Analyses for Shouts at Moves

Total Shouts Received and Number of Moves Receiving Shouts are highly positively correlated, at 0.89 ($p < 0.001$). Given the correlation between these two measures, both are statistically significantly but weakly correlated to the anthropometric measure of a user's Median BMI (0.13, $p = 0.01$ for each of Total Shouts Received and Number of Moves Receiving Shouts), and a user's Median Body Weight ($r = -0.13$, $p = 0.01$ for Number of Moves Receiving Shouts and $r = -0.14$, $p = 0.01$ for Total Shouts Received). *None of the shout measures are statistically significantly correlated with a user's Fitness Index or Resting Heart Rate*. The Number of Moves Receiving Shouts and Total Shouts Received are both statistically significantly correlated with Login Count ($r = 0.16$, $p < 0.001$ and $r = 0.27$, $p = 0.002$, respectively) and Number of Moves ($r = 0.14$, $p = 0.006$ and $r = 0.15$, $p = 0.004$, respectively).

The results of a stepwise regression of Number of Moves Receiving Shouts on Number of Moves, Gender, Age and the core anthropometric measures (median, maximum and minimum of Rest HR, BMI, Body Weight and Fitness Index) are provided in Table E22. For 372 observations, the model F statistic is 4.61 with 4 and 367 degrees of freedom and a *p*-value of 0.001, which leads to rejection of the null hypothesis that the model predicts the mean Number of Moves Receiving Shouts better than the sample mean of the Number of Moves Receiving Shouts. However, the R square for the model is only 0.04. Generally, *better scores on the fitness measures, Minimum of Fitness Index and Median of BMI, are associated with an increased Number of Moves Receiving Shouts for a user as is the Number of Moves. On the face of it, the fitter, leaner users exercise more using the system and receive more shouts from other users*. Interestingly, in the case of the median of BMI, each increase of 4.5 to BMI leads to an average of one fewer moves-receiving shouts. In our sample, 340 males have an average of 2.9 moves that receive shouts, whereas 32 females have an average of 4.9 moves that receive shouts. A *t*-test of the null hypothesis that males have the same number of sessions receiving shouts as females leads to rejection of that null hypothesis ($t = 2.18$, 370 df, p-value = 0.029).

RQ6

Do users who Create Groups or Belong to Groups login more frequently or exercise more frequently than other users?

Data Analyses for Groups that Users Belong To

The data file Groups is used for the analyses in this section and contains the records of users who have joined common interest groups on the system. These groups tend to grow from a common bond by way of activity, location, organization, family and or friendship ties. Appendix C lists the variables and their descriptions for measures of groups.

Descriptive statistics for Groups Users Belong To

The Users Who Belong To Groups file has 23,449 users who belong to 1,046 groups. Group sizes have an extremely long right tail, with 99 percent of users belonging to groups of less than 1,000, 95 percent belonging to groups smaller than 230 and 90 percent belonging to groups of less than 80. A frequency histogram of group sizes is given for group sizes no greater than 80 is given in Figure 34.

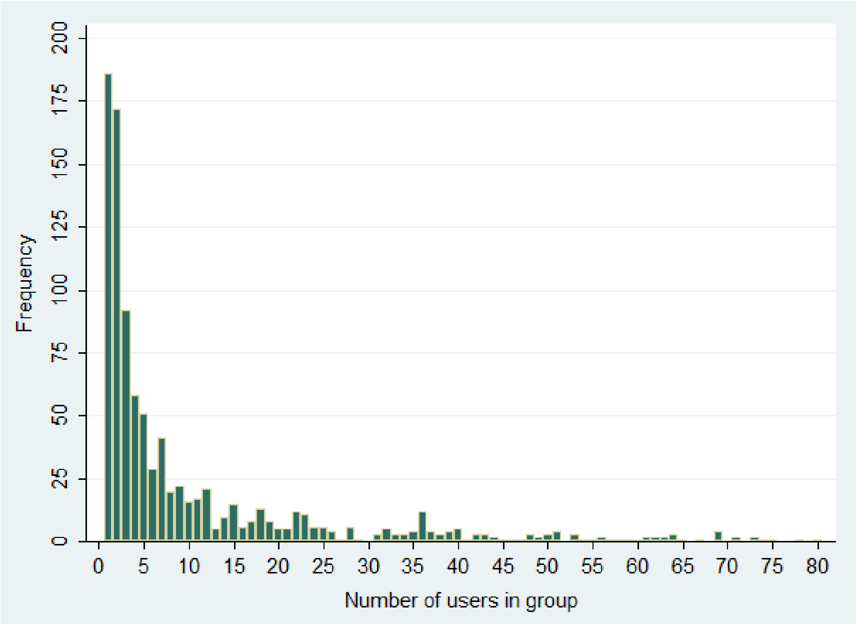

Figure 34. A histogram of groups where Number of User Members <=80

Average group size is about 46 members, but the positive skewness of group size is indicated by the median group size, 19, being well under the average whereas the largest group has nearly 4,000 members. Although more than half of the users belong to only one group, *more than 25 percent of the users belong to at least two groups* and the maximum number of groups a single user belongs to is 48.

Regression Analyses for Groups Users Belong To

Of the 23,349 Users Who Joined Groups, 1,598 can be merged with the Moves and Demographics files. For these users, the correlations between Login Count and Number of Groups Joined is 0.31, and the correlation between Number of Moves and Number of Groups Joined is 0.13, both of which are statistically significant at less than the 0.001 level of significance. These findings are detailed in Table E23.

Table E24 displays the results of a stepwise regression of Number of Groups Joined on Number of Moves, Login Count, Gender, Age and the means of BMI, Weight, Rest HR, and the Fitness Index. The model was estimated on 798 observations and has a model F statistic equal to 7.85 with 6 and 789 degrees of freedom and a *p*-value less than 0.001. The R square for the model is 0.12. All of the fitness variables from Anthropometrics data remain in the model, although their signs *do not provide a clear indication of whether the more fit or the less fit are more likely to join more groups*; no conclusion can be reached on this evidence. For example, a one unit increase in a user's mean BMI increases the average number of groups joined by 0.126 (SE = 0.039, p = 0.001), but a one unit increase in mean Weight decreases the average number of groups joined by 0.030 (SE = 0.009, p = 0.001) and an increase in the Fitness Index Mean increases the average number of groups joined by 0.123 for each one unit increase in Fitness Index Mean (SE = 0.050, p = 0.013). The BMI result suggests the less fit users join more groups, whereas the Weight and Fitness Index Mean results suggest the more fit users join more groups. Age has a small negative effect on the number of groups joined (B = -0.022, SE = 0.009, p = 0.011), and the regression model confirms that males are more likely to join more groups even controlling for Age and Fitness indicators.

RQ6

Do users who Create Groups or Belong to Groups login more frequently or exercise more frequently than other users?

Data Analyses for Users Who Create Groups

The data file used for the analyses in this section contains the records of users who have created common interest groups on the system. These groups tend to grow from a common bond by way of activity, location, organization, family and or friendship ties. A user may create one or many groups. Appendix C contains the table that describes the variables used in this file.

Descriptive statistics for Users Who Create Groups

A total of 331 users who created 379 groups are represented in the Users Who Created Groups file. Users Who Create Groups are more active in the online social activity of Shouting. Table E25 provides a comparison of the descriptive statistics of Users Who Created Groups and members of groups with respect to the shouts made by each. Users who created groups make about twice as many shouts as group members. A *t*-test indicates that this difference is statistically significant at the 0.01 level of significance ($t = 2.55$, $df = 232$, p-value = 0.011).

Table E26 shows the correlations between the Number of Shouts Within a Group by a User Who Created a Group and Login Count, Number of Moves and Age. *Login Count and Number of Shouts are strongly correlated at 0.55*, which is statistically significant at the 0.003 level of significance.

RQ7

Which users most frequently upload exercise sessions and persist the longest in using the device over time, and what characterises these users?

Analyses of the Persistence of Moves Over Time

Panel Data – Negative Binomial Regression Analysis of Moves Over Time

The identification of system usage over time is a key outcome from analysis of the data produced by the active tracking system users under investigation. This measure is determined here as the dependent variable being the number of uploaded exercise sessions (moves) a user has in each of the sequence of numbered months after they start using the system, month 1, 2, 3, 4, and so on for as many months as we have in the data source file. A panel data Negative Binomial Regression was conducted to observe and understand the usage, with the term panel data referring to this cross section as bridging a span of time. The Negative Binomial probability distribution is applicable here because it is only defined for outcomes that are non-negative integers (or counts, also known as count regressions) and we are only able to observe an integer number of workouts in a month. Additionally, the Negative Binomial distribution does not require the variance to be equal to the mean, as does the Poisson distribution, which was originally used here to examine persistence. The data are more dispersed than the Poisson model allows because the Poisson distribution has the variance equal to the mean and most samples including ours tend to have variances greater than the mean.

In the Negative Binomial model, the number of moves in any month *t* for any user *i* follows a Poisson distribution conditional on a parameter γ_{it}, where conditional on another parameter δ_i, γ_{it} follows a gamma distribution with parameters λ_{it} and δ_i and $\lambda_{i,t} = exp(X_{i,t}\beta)$. In the random effects Negative Binomial model, the parameter δ_i is allowed to vary across individuals and $1/(1+\delta_i)$ is assumed to follow a Beta distribution with unknown parameters *r* and *s*. Thus the mean and variance of the number of moves per month for individual users is allowed to vary across users

From the results of the Negative Binomial regression detailed in Table E27, it appears *those users who operate a Flickr account upload more moves per month.* Although initial thoughts were that the novelty of using the new device may wear off with time and with it usage may decline, *the number of uploaded exercise sessions actually increases with the passage of time,* as a statistically significant negative effect on time since first session ($B = 0.070$, $SE = 0.002$, $p < 0.001$) is more than offset by a statistically significant positive effect of time since profile was created ($B = 0.166$, $SE = 0.009$, $p < 0.001$). What seems to be the case from these estimates is that *if a user does not quit working out entirely, then their number of moves tends to increase over time.*

Classification and Regression Tree Analysis (CART) of Move Persistence

The sample of exercise session data used for the purpose of CART analysis under-represents the year 2013 after January 20, 2013. For this reason, January 20, 2013 was chosen as an end of file date for the tree analysis. Further, users whose first exercise session occurred within 90 days of January 20, 2013 were not enrolled long enough to reach a conclusion about persistence and were omitted from the sample, leaving a sample of 225 users who had the necessary exercise session, demographic and anthropometric data.

Persistence here is defined as having at least one move within 60 days of the end of the file cut-off date. The aim of the tree analysis (CART) is to find groups of attributes that classify users as either *persistent* or *not persistent* by this definition, and therefore a binary definition of persistence is required in order to use the CART methodology. Although the use of a 60 day gap between moves is an admittedly arbitrary and perhaps too permissive definition of persistence, the gaps of time in the data do not allow continuous monitoring of exercise gaps and the 60 day gap aims towards conservatism.

The aim of the tree analysis (CART) is to find groups of attributes that classify users as either *persistent* or *not persistent* by this definition. Attributes include the following: Gender, indicator variables for a YouTube channel, Flickr account, Twitter account, Facebook account, a user who makes Shouts, a user who is Shouted At, a user who Belongs to a Group, a user who has an average Training Effect (TE) greater than 4 (roughly the top 10 percent of exercise intensity for this sample), a user who Receives Thumbs, a user who Gives Thumbs, and quartiles of Age, average of Fitness Index and Maximum of Weight. In effect a cross section of attributes that represent a number of possible variable bundles that can provide an indication of system-specific online sociability and fitness. The tree analysis was performed in R version 2.15.1 using the *rpart package*. The quartiles of Age, the mean of a user's Fitness Index and the Maximum of their Weight is given in Table E28. As a guide, the First quartile of Age is all ages less than or equal to 31, the Second quartile consists if users of age 32 to 38, the Third quartile of users of age 38 to 45, and the Fourth quartile comprises all users older than 45.

A graph of the tree is presented as Figure 35. Broadly speaking, the tree first finds *groups of users who are most fit. These users exercise persistently regardless of* *what else is true about them*. The next set of splits is based on whether the user is *sociable* (engages in online social interactions within the system as well as with external online social networks) and *these users exercise persistently*. After finding that mature users are persistent, the tree deals with the remaining users, who are people who are in the bottom half of average Fitness index, and makes leaves that are either based on small numbers or do not diverge much from a 50-50 split into Persistent:Not Persistent users. These last leaves in the tree that classify users in the bottom half of the Fitness Index are probably the least reliable because they are based on fairly small numbers of people remaining to be classified.

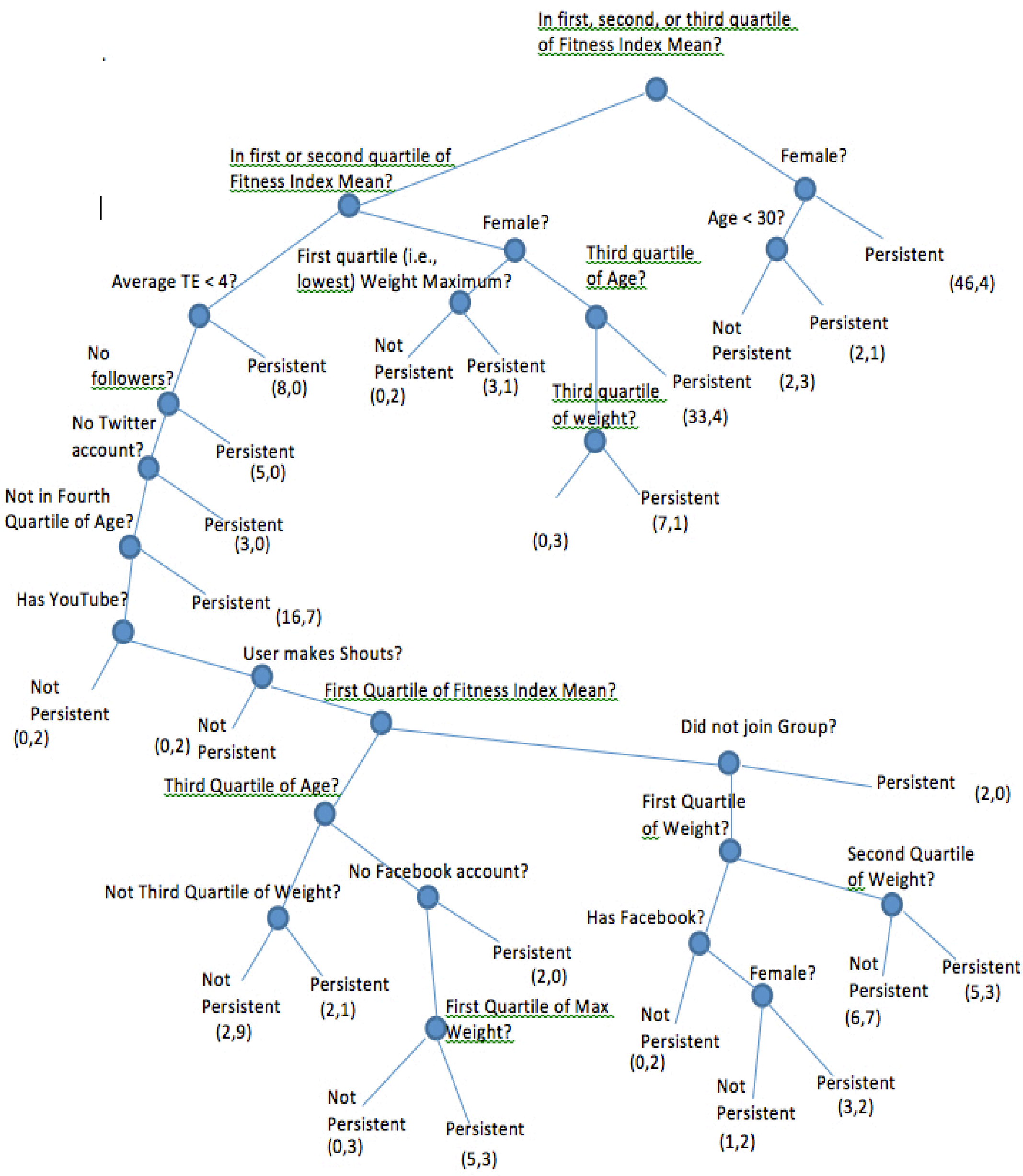

Figure 35. CART tree of Exercise Persistence (#Persistent, #Not Persistent) at leafs.

The left branch is always = yes response to the question at the node.

Explanation of CART tree for Exercise Persistence

The Most-Fit Users: Users in the Third and Fourth Quartiles of the Average of Fitness Index

Two of the first three nodes of the tree sort users by their Average Fitness Index. The root node of the tree splits people into the top quartile of Average Fitness Index and first three quartiles of Average Fitness Index. The right branch out of the root node indicates that *regardless of other attributes, males in the highest quartile of average Fitness index and females in the highest quartile, except for the youngest females (i.e., under 30 years old), persistently exercise.*

The left branch out of the root node is for users in the first through third quartiles of Average Fitness Index, but immediately splits this group into a group that is the lowest 50 percent of the Average Fitness Index (i.e., the first and second quartiles) and the third quartile of the Average Fitness Index. For users in the third quartile (right branch out of this node) the next split is by Gender. For Females in the third quartile of the Average Fitness Index, Females in the first quartile of Weight are not persistent in working out, whereas Females in all other quartiles of Weight and the third quartile of the Average Fitness Index are persistent in working out. For Males in the third quartile of Average Fitness Index, Males who are not in the third quartile of Age persistently work out, and Males who are in the third quartile of Age persistently workout if they are not also in the third quartile of Maximum Weight.

Summarizing, *the majority of people who are in the top 50 percent of the Average Fitness Index persistently exercise regardless of their sociability*. These users are in the top 50 percent of the Average Fitness Index because they work out but the direct benefit they receive from using the exercise device is difficult to assess.

The Least Fit Users: The First and Second Quartile of Average Fitness Index

The first node for users in the first and second quartile of Average Fitness Index splits on the intensity of the workout, where the Average TE of a workout session is greater than 4 is used to create the split. These are users whose moves are in approximately the highest 10 percent of intensity measured by Average TE. Many of these fairly intense moves are already accounted for by people in the third and fourth quartile of Fitness Index, but any users who are in the lowest 50 percent of Average Fitness Index and have these most intense moves define an additional group of fairly fit users who persistently workout.

The next node, *for users in the first and second quartile of Average Fitness Index who do not have the most intense moves, splits on whether the user has Followers or not, with users Who Have Followers persistently working out.*

For users who are in the lowest 50 percent of Average Fitness Index, do not have the most intense workouts and have no Followers, the next split is on whether the user has a Twitter account. *Users in this group who have a Twitter account persistently work out*.

Users who are in the lowest 50 percent of Average Fitness Index, do not have the most intense moves, Have No Followers and Have No Twitter account are next split by age into the fourth quartile of Age and the first three quartiles of Age. *The subset of users in the fourth quartile of Age works out persistently*.

Users who are in the lowest 50 percent of Average Fitness Index, do not have the most intense moves, Have No Followers, Have No Twitter account and are in the first three quartiles of Age are next split on whether they have a YouTube channel, with users who have a YouTube channel being not persistent in exercise.

The only remaining leaf where a substantial number of users are split unevenly occurs for users who are in the first quartile of the Fitness Index mean (i.e., the least fit users), the third quartile of Age, and other than the third quartile of Weight, which has a leaf consisting of two persistent users and nine non-persistent users.

In general, the CART analysis indicates that people who are at the highest levels of fitness as measured by the fitness index work out persistently, and those who are not at the highest levels do not tend to be as persistent. That users who also use social media tend to persist in workouts is consistent with the social media features of the device encouraging workouts, although the CART analysis does not establish a causal link.

Summary of Findings

RQ 1

What are the most popular types of physical activities recorded and uploaded by users of an activity tracker device to their vendor-specific online social network and software service?

The most popular physical activities are Not Specified (34.51%), Running (28.30%) and Cycling including mountain biking (8.85%).

RQ 2

What are the main demographic anthropometric characteristics of the cohort as recorded by the activity tracking system?

The population dataset comprises a gender split of 89.36% Male and 10.64% Female members. The users of the system have a mean age of 39.3 and logged into the system an average of 7.37 times each for the duration covered by the data source files. However, 95.9% have fewer than 40 Logins and 0.61% has 100 or more

Logins. With a mean BMI of 24.88 and a Mean Fitness Index of 5.7 (indicating an average exercise regime of 1 to 3 hours per week), the cohort is best described as reasonably fit, relatively lean, regular exercisers.

RQ 3

What level and type of online social interactions has occurred by and between individual members of the population using the systems online social network?

Users interact socially online *within* the movescount.com system by Joining a Group, Giving a Thumbs Up (ostensibly the equivalent of a *lik*e indicated by one user to another user's post on Facebook) to a published Move, posting a *shout* (a comment which can be a general *shout* on the system or a comment directed at a specific user and their published move) and f*ollowing* another user on the system, an activity that may or may not be reciprocated. The mean number of people a user follows is 3.11 with a standard deviation of 9.362. The number of people a user is followed by has a mean of 1.71 and a standard deviation of 7.4.

Analyses reveal that although the coefficient is sensitive to the number of outliers included, there are generally more than 6 additional logins for each additional follower. Also, the Number of Moves made by a user increases by 4.728 with each additional follower. On average, users receive 2.5 thumbs, and on average 72% of thumbs indicate self-appreciation or self-affirmation. More than 75% of users received two thumbs or fewer and only receive thumbs from themselves. The data for thumbs sent reflect the same phenomenon, as more than 75% of users send 2 or fewer thumbs and only send thumbs to themselves. This indicates a strong preference for a majority of users to self-affirm their exercise efforts using the Thumbs function. A relatively small number of users make an average of 4.5 shouts each to a larger group of receivers who receive an average of 1.9 shouts each. Each of these distributions is extremely positive skewed, as is evidenced by more than half of the users making and receiving only one shout. Users with 5 or fewer shouts made/received account for more than 90% of all users. Users Who Create Groups are more active in the online social activity of Shouting. Infographic summaries of these findings are depicted in figures 41 to 46.

RQ 4

What characterises those users in the population that publish their exercise sessions to Twitter?

Users of the system that publish their moves to Twitter have 5.1 moves more than users who do not Publish to Twitter. Users who Publish to Twitter have an average of 13.2 more logins than people who do not Publish to Twitter.**RQ5**

RQ 5 What association exists between a user's anthropometric characteristics and their published moves in this system?

Generally, better scores on the fitness measures, Minimum of Fitness Index and Median of BMI, are associated with an increased Number of Moves Receiving Shouts for a user as is the Number of Moves. On the face of it, the fitter, leaner users exercise more using the system and receive more shouts from other users. Interestingly, in the case of the median of BMI, each increase of 4.5 to BMI leads to an average of one fewer moves-receiving shouts.

RQ 6

Are there any associations of note in this population that point to a positive role for those users who Create Groups or Belong to Groups?

There emerged strong correlations between the Number of Shouts Within a Group by a User Who Created a Group and Login Count, Number of Moves and

Login Count and Number of Shouts for Group Members. Interestingly, there was also a correlation between Group Membership and Number of Logins, with a weaker but positive association between Group Membership and Number of Moves.

RQ 7

Which users in the cohort most frequently upload exercise sessions and persist the longest in using the device over time and what characterises these users?

If a user does not quit working out entirely, then their number of moves tends to increase over time. Additionally, it appears those users who operate an external social media account upload substantially more moves per month. The majority of people who are in the top 50% of the Average Fitness Index also persistently exercise regardless of their sociability. For users who are in the lowest 50% of Average Fitness Index, those who have a Twitter account persistently work out.

Discussion

In reviewing findings, it bears emphasis that the very low R^2 for most of the correlations found in Study One is neither surprising nor discouraging. The goal of this part of the thesis is to determine whether there are relationships between various variables included in the data set that warrant examination with better models. Given this perspective, from rom the outset, examination of the source data in chapter 3 showed interesting behaviours associated with those users who operate external social media accounts. For example, users who hold YouTube accounts are an average of 0.211 standard deviations of Login Count above users who do not have these accounts (SE = 0.083, p = 0.001).

Certainly, those users that opt to be part of a follow-followed by association with others online seem to both more frequently use the system as measured by the average number of logins and exhibit a greater average number of uploaded exercise sessions. For example, each additional person a user follows is associated with 0.938 additional logins (SE = 0.065, $p < 0.001$), on average. Interestingly, the correlations between the systems use indicators of Login Count and Number of Moves; with the metrics of exercise intensity show only weak positive correlations. It is apparently not the case that the count of Logins or Number of Moves is associated with exercise intensity variables to any large extent, which is to say that how hard the workout is has no bearing on how frequently you login, or uploads exercise sessions to the system. Although the comparatively passive online social activity of following others is quite prevalent the user population showed less enthusiasm for commenting on the activities of others using the *shouts* function, as shown by the finding that users with 5 or fewer shouts made/received account for more than 90 percent of all users. It would seem that these users of an exercise tracking system are content to keep tabs on one another but not necessarily engage with one another online through the exchange of comments. Yet, as observed in a number of analytic processes, the proclivity exhibited by the small subsection of the user population that tweet their uploaded exercise sessions for greater systems usage, exercise upload frequency and persistence if they happen to be less fit shows the use and implications of online social interactions is not simple.

Chapter 5

Introduction

Study Two looks to ascertain, through direct query of a subset of the user population and their interaction with the system design elements, the role of such elements on the relative persuasiveness of the system in relation to the targeted behavioural use of the system; to support exercise activity. Effort was also made to learn more about the regular exercise behaviour of these individuals prior to purchase of their system, identification of some additional demographics, use of the system in everyday exercise regimes and their intention for continued use of the system. Additional effort was expended to better understand the factors that may influence the online social activities of these users and a model produced to explain the associations between the design of the system, user age and marital status, ROPAS scores and intended continued use of the system.

This study seeks to provide answers to the related research questions and satisfy the relevant thesis goals. The research questions for this study address the effects of fitness tracker system design and its encouragement of exercise by augmenting existing structural models in the BCSS literature to account for social media interactions.

Goal Three

To determine the role of pre-existing exercise behaviour on intention to persist using the device

Research Questions

RQ8 What portion of the sample population was actively exercising prior to purchasing the Suunto device and system?

RQ9 How regularly did users indicate they used the device as part of their normal exercise regime?

Goal Four

To create a new scale linking BCSS-PSD to SDT via the ROPAS scale.

Research Questions

RQ10 What were the most popular functions of the movescount.com system in the sample?

RQ11 Does analysis of the movescount.com sample population responses to the BCSS scale reveal consistency with the existing evidence?

RQ12 Does an individual's Relatedness to Others in Physical Activity (ROPAS) score in any way predict the perceived social support and social identification functions of the system?

RQ13 Is there a difference in the ROPAS scores between users who publish exercises sessions to Twitter and those users who do not?

RQ14 What part is played by the factors in the BCSS scale that assess the persuasive elements of the system on the users intention to continue using the system?

RQ15 Can we create a structural model that will represent the association between a user's intent to continue using the system, BCSS persuasive systems design factors, key user demographics, exercise usage, online group membership and prior exercise behaviour?

Methods

A qualitative methods approach was used to augment the analyses of the quantitative data completed on the accrued data from the cohort's use of the system over a 12-month period. To do this, the user population database an online survey was conducted using standardised scales. Of particular interest was the role of the design of the system itself on the relative persuasiveness of the system in relation to the targeted use of the system by the user cohort. Effort was also made to learn more about the regular exercise behaviour of these individuals prior to purchase of their system, some additional demographics, their use of the system in their everyday exercise regimes and their intention for continued use of the system.

The survey-based process was administered via email and the So-Go online survey system. An existing standardised scale for assessing the persuasiveness of system elements based on BCSS, along with the BTOB standardised sub-scale for assessing the Online Sociability of members were used. This was combined with the ROPAS scale for measuring their perceived Relatedness to Others during Physical Activity. This survey process generated the data that was used to answer the research questions for this study based on the following sequence of methods. The logical flow of nethod output to input for each of the following is detailed in the Results section.

1. Descriptive Analysis of Demographics and Exercise Habits
2. Factorial Analysis of Study Population responses to existing BCSS Scale
3. Multivariate Regression Analyses of BCSS Factors
4. Multivariate Analyses of Covariance (MANCOVA) of ROPAS Test Results from Study Population and the BCSS social factors of SOCS and SOID
5. Structural Equation Model (SEM) for Predicting SOCS and SOID Factors
6. Grouping analyses to Understand Types of Social Users and System Use

7. Regression analyses of relationships between all of the constructs in the structural model on a users' *intent to continue using the system for exercise*
8. Construct a Structural Model for Use Continuance
9. Total Effects Analysis of the Structural Model

Invariance testing was used to test for the robustness of all results in study two. To perform invariance testing, two subsamples were created by random assignment[7] and each model was estimated on the full sample and then on the two subsamples. In the results section, any differences in results between the two subsamples are reported along with any differences in results between the subsamples and the full sample. Details of how to acess the electronic files with scripts and datasets for the invariance testing process can be found in Appendix F.

Results

RQ8

What portion of the sample population was actively exercising prior to purchasing the Suunto device and system?

RQ9

How regularly did users indicate they used the device as part of their normal exercise regime?

RQ10

What were the most popular functions of the movescount.com system in the sample?

[7] To randomly assign observations to two subsamples, a random variable that follows a uniform distribution was drawn for each observation using the seed XXX. These numbers were then sorted, and the first 260 observations were placed in group 1 and the last 261 observations were placed in group 2

Demographics and User Exercise Habits

A total of 521 completed surveys were returned using the So-Go survey system. All respondents, members of the vendor's opted-in research database had also given consent for University of Tasmania to survey them; see Appendix A for the UTAS Ethics Approval information. Table 9 summarizes the demographic information provided on the surveys. About 92 percent of the respondents were male and slightly more than three-quarters of the respondents were either married or had a domestic partner. Survey respondents were shown to be a well-educated group, as more than half (53%) have at least some graduate school experience and more than 96 percent graduated high school. Sample sizes were not adequate in each education level group. Thus, for analysis below, education was recoded into a binary variable with a value of 1 if the user had a high school education or less and 0 if their education continued beyond high school. The mean age as of January 1, 2014 was 40.32 years old, with a standard deviation of 9.69 years and a range of 17 years old to 69 years old.

Table 9 *Frequency Table of Respondent Demographics and Exercise Habits*

Variable	Frequency	Percentage(%)
Gender		
Male	477	91.55
Female	44	8.45
Marital status		
Married/Domestic partnership	393	75.43
Single	128	24.57
Education		
Never attended school	1	0.19
Grades 1 to 8(elementary)	3	0.58
Grades 9 to 11(some high school)	14	2.69
Grade 12 or GED (high school graduate)	31	5.95
Grades 9 to 11(some high school)	14	2.69
College 1 to 3 year	56	10.75
College 4 years	138	26.49
Graduate school	278	53.36
Exercise regularly 12 months prior?		
Yes	445	85.58
No	75	14.42
Ever exercised prior (if no to previous)?		
Yes	60	80
No	15	20

Note. $N = 521$

Table 9 also provides responses to the questions on exercise habits prior to purchasing the device. *More than 85 percent of the sample (445/521) had exercised in the year preceding their purchase of the device.* Of the 75 people who had not exercised in the year prior to purchasing the device, 80 percent had exercised at some point in their lives.

There is a clear dichotomy in usage of the device summarized in Table 10. *At least 75 percent of the respondents reported regularly wearing the device, logging into the system and uploading an exercise session (move).* By contrast, for all of the remaining uses of the system (following another user, shouts, thumbs, joining a group), no more than 25 percent of users regularly or frequently engage in these activities, i.e., at least 75% of respondents report never or only occasionally engaging in these activities. *Of the possible sociability uses of the device, the most popular when ranked by the mean is following another user* (M = 1.55, SD = 0.75), followed by joining a group (M = 1.44, SD = 0.67). Again using the mean as an indication of popularity, the least popular other usage of the device is adding a shout or comment to another user's move or to a group.

Table 10 *Device Usage - Core Functionality*.

Question	Mean	Std. Dev	25th	50th	75th
Wearing the device to record an exercise session	3.63	0.62	3	4	4
Logging into the online system	3.19	0.82	3	3	4
Uploading an exercise move to the online system	3.22	0.87	3	3	4
Adding a shout comment to your own move	1.40	0.72	1	1	2
Adding a shout comment to another person's move	1.26	0.57	1	1	1
Following another user on the online system	1.55	0.75	1	1	2
Giving a thumb to another user's move on the online system	1.32	0.61	1	1	2
Join a group online	1.44	0.67	1	1	2
Add a shout comment to a group	1.20	0.49	1	1	1
Downloading an app online to use with your device	2.00	0.85	1	2	2

Note. 4 item Likert style: 1- Never; 2- Occasionally; 3- Regularly; 4- Frequently

RQ11

Does analysis of the movescount.com sample population responses to the BCSS scale reveal consistency with the existing evidence?

Factor Analysis and the Relationship with Previous Research: Number of Factors and Constructs

All of the items included in the survey have appeared in previous research except the questions created to address current system use behaviours that were added to understand the current practices of respondents in terms of systems functionality. The Relationship to Others in Physical Activity Scale (ROPAS) was developed by (Wilson & Bengoechea, 2010) and has been used extensively, (Standage, Gillison, Ntoumanis, & Treasure, 2012). It indicates the degree to which exercise is a social activity for an individual in a real world only. For example, a respondent who plays a team sport or a competitive sport with another person or persons may consider exercise as part of their social life. As a measurement device, it was never designed to connect offline physical activity social proclivities with a user's online behaviour. Johnson & Kulpa (2007)) developed the Online Sociability Scale (O_SOC) for assessing an individual's perceived sociability in an online setting, the Internet. Online sociability indicates usage of the Internet for communications such as email and meeting with others, but does not reflect sophisticated use of social media such as Twitter, YouTube or Flickr and is not directly related to exercise. Online sociability is included here to indicate at least moderate familiarity with and usage of the Internet for social purposes. Each of these is a single factor scale.[8]

The largest number of survey items is drawn from the Behavioral Change and Support Systems (BCSS) scale developed by Lehto and Oinas-Kukkonen (2014). This primary component of the survey has been used at least twice in published papers; Stibe & Oinas-Kukkonen, 2014 and Lehto et al., 2012. It is worthwhile to review previous findings from the exploratory factor analysis for these items in at least one study. Note that these factors are re-examined as part of the structural equation modelling done to investigate user continuance; RQ 15 later in this chapter. Table 11 indicates the eight factors found in these items by Lehto and Oinas-Kukkonen (2014), which may be briefly described as follows:

[8] For example, for ROPAS, principal component analysis yields an eigenvalue of 5.03 for the first principal component and 0.33 for the second principal component. Cronbach's alpha for the six reliability items is 0.96. For online sociability, the first principal component has an eigenvalue of 2.05 and the second principal component has an eigenvalue of 0.89. Cronbach's alpha for the Online Sociability items is 0.63.

- **Use Continuance** (CONT) user's intention to continue using the system in the future
- **Perceived Credibility** (CRED) user's judgment about the credibility of the system, encompassing "trust, believability, reliability and credibility" (Lehto and Oinas-Kukkonen 2014)
- **Computer-Human Dialog Support** (DIAL) user's judgment about the dialog support provided by the system
- **Perceived Effectiveness** (EFFE) user's judgment on how helpful the system is in performing activities (e.g., recording workout metrics)
- **Perceived Effort** (EFFO) user's judgment about the effort required to use the system
- **Primary Task Support** (PRIM) user's judgment on how well the system supports the user's achievement of goals through facilitating goal setting and tracking, adapts to user's needs and promotes the user's self-efficacy
- **Perceived Social Support** (SOCS) user's judgment on how well the system facilitates receiving/providing social support for their/other's fitness goals
- **Social Identification** (SOID) reflects the user's identity with other system users and the extent to which they share interests, characteristics, and language and feel part of a user community.

Table 11 *Eight Factor Solutions for BCSS.*

Item		Factor label
bcss_s	I am not going to use the system from now on (reverse)	CONT
bcss_ab	I am going to continue using the system	CONT
bcss_f	In my opinion, the provided content is trustworthy	CRED
bcss_g	Overall, I consider the system accurate	CRED
bcss_k	In my opinion, the provided content is professional	CRED
bcss_n	In my opinion, the provided content is believable	CRED

bcss_r	Overall, I consider the system believable	CRED
bcss_w	Overall, I consider the system professional	CRED
bcss_x	In my opinion, the provided content is accurate	CRED
bcss_z	Overall, I consider the system trustworthy	CRED
bcss_a	The system encourages me.	DIAL
bcss_d	The system provides me reminders for reaching my personal goals.	DIAL
bcss_j	The system provides me with appropriate feedback.	DIAL
bcss_t	The system rewards me.	DIAL
bcss_p	My chances of exercise regularly improve by using the system	EFFE
bcss_v	In my opinion, using the system has an effect on my exercise behaviour	EFFE
bcss_e	Using the system is difficult for me (reverse)	EFFO
bcss_h	Using the system does not require a lot of effort from me	EFFO
bcss_o	Using the system is straightforward for me	EFFO
bcss_b	The system helps me in keeping track of my progress	PRIM
bcss_m	The system helps me in reaching my goals gradually	PRIM
bcss_y	The system makes it easier for me to reach my goals	PRIM
bcss_l	Learning from my peers' actions is beneficial for me	SOCS
bcss_u	I get support from my peers through the system when I need it	SOCS
bcss_aa	Through the system, I can share my experiences with my peers	SOCS
bcss_c	I consider other users of the system as my peers	SOID
bcss_i	I do not care about the other users of the system	SOID
bcss_q	It is easy for me to relate to other users' experiences	SOID

Note. Source: Lehto and Oinas-Kukkonen (2014)

Scales for constructs were computed as the simple averages of the responses to each item contained in a construct. Summary statistics of the scales for constructs covering the BCSS items and internal reliability as measured by Cronbach's alpha are presented in Table 12, along with the two single additional factors measured, ROPAS and BTOB (online sociability sub scale expressed as O_SOC). The reliability measures range from 0.56 (CONT) to 0.96 (ROPAS). As known, test length has an impact on reliability score of the scale. The CONT factor includes only 2 items and this may be one of the reasons for the low reliability score of this construct. Adequate item loadings were one reason for treating reliability score of CONT construct as acceptable. The other reason was that previous research (Lehto & Oinas-Kukkonen, 2014) revealed that these factors matter in the evaluation of Behavioral Change Support Systems. One of the aims of this study was to test the previous research results with a different kind of BCSS system, that which serves an exercise community instead of web-based weight loss and alcohol control communities as found in the literature. This is why the first part of Study 2 explores relationships similar to those explored by previous authors and uses the same constructs defined by previous authors (Lehto & Oinas_Kukkonen, 2014). This is regarded as a valid and efficient method for improving the existing knowledge base and to permit an appropriate study comparison, (Boudreau, Gefen, & Straub, 2001).

Table 12. *Summary Statistics for the 8 Factor Solution*

Scales	Mean	SE	t	p	25th	50th	75th	Cronbach α
ROPAS_ave (6-likert)	3.69	0.06	11.50	<0.001	2.67	4.00	4.83	0.96
O_SOC_ave (5-likert)	2.72	0.03	-9.33	<0.001	2.40	2.80	3.20	0.63
BCSS constructs* - (8- likert)								
DIAL_ave	3.40	0.03	13.33	<0.001	3.00	3.50	4.00	0.66
PRIM_ave	3.86	0.03	28.67	<0.001	3.67	4.00	4.33	0.79
EFFE_ave	3.62	0.04	15.50	<0.001	3.00	4.00	4.00	0.77
SOCS_ave	2.93	0.04	-1.75	0.081	2.33	3.00	3.67	0.72
SOID_ave	2.82	0.04	-4.50	<0.001	2.33	3.00	3.33	0.72
CRED_ave	3.99	0.02	49.50	<0.001	3.88	4.00	4.13	0.90
EFFO_ave	4.04	0.03	34.67	<0.001	4.00	4.00	4.33	0.76
CONT_ave	4.36	0.03	45.3	<0.001	4.00	4.50	5.00	0.56

Note. *DIAL = Dialogue support; PRIM = Primary task support; EFFE = Perceived effectiveness; SOCS = Social support; SOID = Social identification; CRED = Perceived credibility; EFFO = Perceived effort; CONT = Continuance intention

For the BCSS constructs, given that a score of 3.0 is neutral for the five-response Likert scale used for items, we can locate the constructs' population means as either comfortably above neutral or significantly less than neutral. The constructs that are statistically significantly above a neutral rating include CONT, EFFO, CRED, PRIM, EFFE and DIAL. Sample *t* statistics and *p* values can be seen in Table 13. The two social items, SOCS and SOID, have sample means that imply that the population means are less favourable than a neutral rating. Interestingly, from the ensuing analyses, the sample mean of ROPAS suggests that *on average, people do* *engage with others as they exercise to a moderate extent, whereas the sample mean for O_SOC suggests that on average, the group does not socialize online as much as the median value of the scale*.[9]

Given the internal consistency of the eight factor solution as evidenced in the literature and an inability to use eight factors in a structural equation model as constructs represented by latent variables then multivariate analysis of variance and multiple regression approaches are employed here on the scales to explore relationships similar to those explored by previous authors.

Relationships Among Constructs in Previous Research

In the structural equation model proposed by Lehto and Oinas_Kukkonen (2014), intention to continue using (CONT) is determined by users' perceptions of the effectiveness of the system (EFFE), the effort required to use the system (EFFO), the credibility of the system (CRED), and the social support offered by the system (SOCS). In turn, perceived effectiveness of the system and perceived effort required to use the system are functions of primary task support (PRIM). We explore whether the same relationships hold in our data as were found by Lehto and Oinas-Kukkonen (2014) through the use of regression analysis of the scales whose summary statistics were presented in Table 12.

Correlations among the scales for constructs are depicted below in Table 13. All of the constructs have significant correlations except O_SOC and DIAL, O_SOC and EFFO and O_SOC and CRED. Observe that there are especially strong correlations between SOCS and SOID ($r = 0.745$, $p < 0.001$), PRIM and EFFE ($r = 0.625$, $p < 0.001$) and PRIM and DIAL ($r = 0.641$, $p < 0.001$) and DIAL and EFFE (r

[9] The online sociability scale is not normed to any group in the paper that first published and validated it and no norm was found for it.

= 0.592, p < 0.001). PRIM and CRED are also correlated at more than the 0.5 level. From the survey data, effectiveness (EFFE) is strongly correlated with primary task support (PRIM), dialog support (DIAL) and effort (EFFO).

Table 13 *Correlations Among Construct Scales*

Scale average	CONT	PRIM	EFFE	DIAL	SOCS	SOID	EFFO	CRED	ROPAS	OS
1.CONT	1.000									
2. PRIM	0.338^{+}	1.000								
3. EFFE	0.313^{+}	0.625^{+}	1.000							
4. DIAL	0.216^{+}	0.641^{+}	0.592^{+}	1.000						
5. SOCS	0.119**	0.339^{+}	0.354^{+}	0.407^{+}	1.000					
6. SOID	0.126**	0.291^{+}	0.356^{+}	0.403^{+}	0.745^{+}	1.000				
7. EFFO	0.452^{+}	0.417^{+}	0.318^{+}	0.362^{+}	0.124**	0.117**	1.000			
8. CRED	0.394^{+}	0.501^{+}	0.371^{+}	0.425^{+}	0.228^{+}	0.152^{+}	0.483^{+}	1.000		
9. ROPAS	0.128**	0.157^{+}	0.184^{+}	0.174^{+}	0.293^{+}	0.333^{+}	0.106*	0.147^{+}	1.000	
10. O_SOC	0.117**	0.119**	0.050^{+}	0.073	0.130**	0.195^{+}	0.002	0.049	0.161^{+}	1.000

*Note: *p < 0.05, **p < 0.01, $^{+}$p < 0.001*

Table 14 depicts the supporting role played by primary task effectiveness (PRIM) in users' perceptions of the effectiveness of the system (EFFE) and the effort required to use the system (EFFO). The relationship was examined in two steps. The overall effect of PRIM on both of the constructs was investigated via the multivariate analysis of covariance (MANCOVA) and results revealed a significant multivariate effect for the two latent variables, (*Roy's largest root* = 0.798, $F(2, 518) = 206.54$, $p < 0.001$). Univariate analyses for the effect of primary task effectiveness was performed via multiple regression analysis. Results indicated in both cases for the 521 observations in the sample *there is overwhelming support for the same positive relationship between the scales for PRIM and EFFE* ($B = 0.825$, $SE = 0.045$, $p < 0.001$) and PRIM and EFFO ($B = 0.419$, $SE = 0.040$, $p < 0.001$) *as found by earlier authors* among the latent constructs in their structural equation models. Consistent with BCSS theory, *a system's effectiveness is strongly driven by its ability to enable* *users to complete primary tasks and the effort required to do this is perceived to be not insurmountable by the user*. Qualitatively similar results were obtained in each of the subsamples used for invariance testing.

Table 14 . *Multivariate Regression Estimates for EFFE Average and EFFO Average Regressed on PRIM Average*

	Coeff.	Std. Err.	t	P>|t|	95% LCL	95%UCL
EFFE average						
PRIM average	0.825	0.045	18.25	0.000	0.737	0.914
Constant	0.437	0.177	2.46	0.014	0.089	0.786
EFFO average						
PRIM average	0.419	0.040	10.44	0.000	0.340	0.498
Constant	2.423	0.157	15.41	0.000	2.114	2.732

Multivariate regression analyses of BCSS Factors

As discussed previously, the results of the structural equation models referenced in existing literature shows that the perceived social support (SOCS) provided by the system also entices users to continue using the system, (Lehto & Oinas-Kukkonen, 2013; Stibe et al., 2011;Stibe & Oinas-Kukkonen, 2014) . In turn, perceived social support is determined by the level of dialog support (DIAL) the system provides and the extent to which it cultivates identification among users as a group with shared characteristics and goals (SOID); in effect, this could be argued to be a measure of homophily. Here, a simple regression of the scale for SOCS on the scales for DIAL and SOID are reported in Table 15. Again, both of the relationships are positive with *t* statistics that easily surpass conventional thresholds for statistical significance. SOID has a large effect on SOCS, with an estimated coefficient of 0.698 (R^2 = 0.49). On the other hand, DIAL can explain only 2% of the variance in SOCS scores and has a small effect despite the significance. Qualitatively similar results were obtained in each of the subsamples used for invariance testing.

Table 15 *Regression Estimates for SOCS Average Regressed on DIAL Average and SOID Average*

	Coeff.	Std. Err.	t	P>|t|	95% LCL	95%UCL
DIAL average	0.154	0.045	3.38	0.001	0.065	0.244
SOID average	0.698	0.033	20.90	0.000	0.633	0.764
Constant	0.444	0.134	3.31	0.001	0.180.	0.706

Although the Relatedness to Others in Physical Activity Scale (ROPAS) is not included in the structural equation models evident in the literature, because it measures a propensity to relate to others in physical exercise, we would anticipate a positive relationship between ROPAS and both of the social constructs, SOCS and SOID. The overall effect of ROPAS on SOCS and SOID was examined via multivariate analyses of covariance (MANCOVA). Results indicated that *ROPAS has a significant effect on the construct*s (*Wilk's lambda* = 0.885, $F(2,518) = 518$, $p < 0.001$). In the second step, univariate effects were examined via the multiple regressions of the scales of SOCS and SOID on ROPAS. Table 16 presents regression coefficients for the analysis. It reveals a statistically significant positive relationship, but the effect sizes are small for both of them ($r = 0.165$ and $r = 0.187$). Qualitatively similar results were obtained in each of the subsamples used for invariance testing.

Table 16 *Regression Estimates for SOCS Average and SOID Average Regressed on ROPAS Average*

	Coeff.	Std. Err.	t	P>|t|	95% LCL	95%UCL
SOCS average						
ROPAS average	0.165	0.024	6.97	0.000	0.119	0.212
Constant	2.324	0.094	24.67	0.000	2.139	2.509
SOID average						
ROPAS average	0.187	0.023	8.05	0.000	0.141	0.232
Constant	2.126	0.092	23.05	0.000	1.945	2.308

As expected, high scores on the Relatedness to Others in Physical Activity Scale (ROPAS) predicts high scores on perceived social support (SOCS). However, ROPAS is not specifically related to any exercise data system or online social network so much as it is a reflection of face-to-face contact during exercise. Therefore, *social identification with a social community that uses the device may be a prerequisite for ROPAS to have any effect on social support*. It's hypothesized that users' social identification scores (SOID) will mediate the relationship between ROPAS and SOCS scores and mediation analysis conducted, (Baron & Kenny, 1986; Cole & Maxwell, 2003; Imai, Keele, & Tingley, 2010).

RQ12

Does an individual's Relatedness to Others in Physical Activity (ROPAS) score in any way predict use of the perceived social support (SOCS) and social identification (SOID) functions of the system?

Both structural equation and mediation analysis were used to answer this. For brevity and consistency with the approach used to answer RQ15 later in this chapter, the SEM solution is included here and an alternate Sobel test for mediation is detailed in Appendix J including a model.

Structural equation model for ROPAS prediction of SOCS and SOID

To test the probable mediator role of SOID, the direct and indirect effects of dependent variable (ROPAS) on the independent variable (SOCS) were examined via structural equation modelling. Standard errors were bootstrapped for 1,000 samples in order to receive robust results. Maximum likelihood was used as the method. Several indicators of model adequacy are assessed. First, the Wald tests for the null hypothesis that all coefficients are equal to zero all have *p* values less than 0.01, which implies that the models perform better than sample means at prediction. The second adequacy indicator is the goodness fit of the model. Standardized root mean squared residual (SRMR) value is equal to 0.00 and these indicate an overall good fit for the model. Thirdly, R^2 for SOCS variable and SOID variable were found to be 0.56 and 0.11, respectively and R^2 value for overall model was found as 0.12. While SOCS variable has a high R square value, results must be considered cautiously because of the low R square value of the overall model.

Estimates for the model are represented in Table 17. Results show *a positive effect of ROPAS on SOID and a positive effect of SOID on SOCS* were significant at less than 0.001 level of significance, while the positive effect of ROPAS on SOCS was not found to be statistically significant when measured together with SOID. Table 18 provides estimates of the direct, indirect, and total effects of the ROPAS. Ratio of the indirect effect to the sum of direct and indirect effect is 0.83 showing that *83% of the effect of ROPAS on SOCS is directed via SOID*. Qualitatively similar results were obtained in each of the subsamples used for invariance testing.

Table 17 *Estimated Coefficients for the Structured Model.*

	Coeff.	SE	z	p>|z|	95% LCL	95% UCL
SOID						
ROPAS	0.187	0.023	8.05	0.000	0.141	0.232
Cons	2.126	0.092	23.05	0.000	1.945	2.308
SOCS						
SOID	0.733	0.031	23.48	0.000	0.672	0.795
ROPAS	0.028	0.018	1.63	0.104	-0.006	0.063
Cons	0.765	0.093	8.19	0.000	0.582	0.949

Table 18. *Direct, Indirect, and Total Effects of ROPAS.*

	Coeff.	Bootstrapped SE	95% LCL	95% UCL
Direct Effect	0.028	0.024	-0.020	0.073
Indirect Effect	0.137	0.024	0.088	0.183
Total Effect	0.165	0.032	0.102	0.227

Deeper analysis of the Social Features of the System

The use of the social features of the system was further explored by the creation of different groups of users using indicator variables that have a value of 0 or 1, a useful function of the statistical package, STATA 13 used in this instance to help identify and model levels and types of social media activity by users. The groups were organised as follows:

1. **NO_ACCOUNTS.** A No Accounts value of 1 is given if the user does not indicate that they have a Facebook, Twitter, YouTube, or Flickr account when they create their profile for the system and 0 is given if the user indicates that they do have any of these external social media accounts.

2. **Use of the movescount.com social network**. We first created a variable, **ONLINE_ACTIVITY_SUM**, that is the sum of the respondent’s replies to five items from the Usage subscale that are related to the in-house social networking

functionality of the movescount.com site of social features of the device. The questions that were summed together were: adding a shout, following a user, giving a thumb, joining a group, and adding a shout to a group. Observe that responses for the usage questions are 1-Never, 2-Occasionally, 3-Regularly and 4-Frequiently. This means the minimum possible value is 5 for a user who never does any of these things and the maximum possible value is 20 for a user who frequently does all of these things. Table 19 reveals the correlation coefficient values between Online_Activity_Sum and the other constructs that used in this study. All constructs except EFFO, CRED, and CONT have a significant positive relationship with Online_Activity_Sum. As expected, the highest relationship is held between social constructs (SOCS and SOID) and Online_Activity_Sum, with 0.466 and 0.510, respectively. Two groups of respondents were created in terms of their online_activity_sum scores in order to make comparative analyses between these groups. A value of 10 implies an average score of 2, which in turn implies only occasional use of the features on average. Therefore we used 10 as a threshold to create two groups of respondents: Users were put into the "**Social User** (**USER**)" group if they scored more than 10 on ONLINE_ACTIVITY_SUM and they put into the "**Social Nonuser** (**NONUSER**)" groups if they scored equal or less than 10. To be in the **USER** group, a respondent would have to use at least one social feature of the device regularly.

Table 19. *Correlation Coefficients Among Construct Scales and Online_Activity_Sum.*

	Online_activity_sum	Significance
SOCS	0.466	<0.001
SOID	0.510	<0.001
EFFE	0.150	<0.001
EFFO	0.076	0.085
DIAL	0.156	<0.001
PRIM	0.101	0.022
CRED	-0.001	0.840
CONT	0.043	0.332
ROPAS	0.204	<0.001
O_SOC	0.169	<0.001

It is expected that users who have an account in at least one of the external social platforms will tend to be in the **USER** group, and users who have no account in any of the external social platforms will tend to be in the **NONUSER** group. However, we want to explore whether the system changes people's behavior. For this reason, we created two groups of people from these variables.

3. **UNEXPECTED USERS**: have a 1 for NO_ACCOUNTS, but also 1 for USER. In other words, *people who have no social media accounts when their profile is created but use at least one of the social networking functions of the movescount.com site regularly*. Perhaps surprisingly, there are 55 UNEXPECTED USERS in the sample. While it cannot be concluded that the device enticed them into their first use of social media, clearly the use of social media in conjunction with the device seemed attractive to these people.

4. **UNEXPECTED NON-USERS**: have a 0 for NO_ACCOUNTS but 1 for NON-USER. In other words, these *are respondents who had at least one social media account at the time their profile was created, but do not tend to use the social networking functions associated with movescount.com*. There are 62 UNEXPECTED NON-USERS.

A variety of *t*-tests were run with each of these groups against the remainder of the sample. The first test is for Login Counts. We find a significant difference between the mean login count of UNEXPECTED NON_USERS (M = 18.68, SE = 4.08) and the full sample (M = 9.24, SE = 1.00) that favours UNEXPECTED NON_USERS ($t(519) = -3.042$, $p < 0.01$). We obtained a similar result for a *t* test of the Number of Moves, with UNEXPECTED NON_USERS (M = 12.13, SE = 2.09) being statistically significantly higher than the Number of Moves recorded by the rest of the sample (M = 7.92, SE = 0.72 and $t(519) = -1.998$, $p < 0.05$).

The next test examined the Fitness Index Mean for UNEXPECTED USERS against the rest of the sample. There were only 113 observations for the Fitness Index Mean, and only 8 of them are in the UNEXPECTED USERS group. Nonetheless, the between subjects *t*-test result revealed that UNEXPECTED USER'S fitness index mean (M = 6.92, SE = 0.34) is significantly higher than the rest of the sample (M = 5.96, SE = 0.13), $t(111) = -1.993$, $p < 0.05$. However, these results must be regarded with some caution because of the unbalanced and small sample size.

Next tested was the average of the responses for the factors SOCS, SOID, and EFFE measures for UNEXPECTED USERS against first, the remainder of the full sample, and then against the UNEXPECTED NON-USERS. Once again, there are 521 observations with 55 in the UNEXPECTED USERS group. Results indicated that the SOCS mean of UNEXPECTED USERS group (M = 3.70, SE = 0.10) is significantly higher than SOCS mean of rest of the sample (M = 2.84, SE = 0.04, $t(519) = -7.586$, $p < 0.001$). Similarly, the SOID mean of UNEXPECTED USERS group (M = 3.62, SE = 0.08) is significantly higher than SOID mean of rest of the sample (M = 2.72, SE = 0.04, $t(519) = -8.094$, $p < 0.001$. Finally, the EFFE mean of

UNEXPECTED USERS group (*M* = 3.95, *SE* = 0.12) is significantly higher than EFFE mean of rest of the sample (*M* = 3.58, *SE* = 0.04, $t(519) = -2.814$, $p < 0.01$).

In a second round of comparisons, the two extreme groups are compared with each other with respect to differences in scale variables for all of the constructs. The sample size for UNEXPECTED USERS is 55 and it is 62 for UNEXPECTED NON-USERS. A *t*-test was conducted to search for differences between the two groups for each of the nine constructs ROPAS, SOCS, SOID, O_SOC, PRIM, DIAL, EFFE, CRED, and EFFO. A Bonferroni correction was used in order to control Type 1 error given the relatively large number of tests done using these groups. Using the Bonferroni correction, a significance level of 0.05 is divided by 9 and therefore we require a *p* value of 0.006 or less to reject the null hypothesis at the significance level of 0.05 for the family of tests given the number of hypothesis tests being conducted. The results indicated that there is no difference between these two groups in terms of PRIM, CRED, DIAL, EFFO, and O_SOC scores. UNEXPECTED USERS (*M* = 3.95, *SE* = 0.12) have higher average scores on EFFE than UNEXPECTED NONUSERS (*M* = 3.49, *SE* = 0.14) at the 0.013 significance level, which still does not survive the Bonferroni correction. Even with the Bonferroni correction, significant differences between these two groups were found for ROPAS ($t(115) = -2.777$, $p < 0.01$) , SOCS ($t(115) = -5.421$, $p < 0.001$), and SOID ($t(115) = -6.615$, $p < 0.001$) scores. In all of these measures, Unexpected Users earned a significantly higher score than Unexpected Nonusers as detailed in Table 20.

Table 20 *t Tests between UNEXPECTED USERS and UNEXPECTED NON-USERS*

	Mean	SE	t	df	sig.
ROPAS			-2.777	115	0.006
Unexpected Nonuser	3.62	0.20			
Unexpected User	4.34	0.16			
SOCS			-5.422	115	0.000
Unexpected Nonuser	2.91	0.10			
Unexpected User	3.70	0.10			
SOID			-6.615	115	0.000
Unexpected Nonuser	2.72	0.11			
Unexpected User	3.62	0.08			

RQ13

Is there a difference in the ROPAS scores between users who publish exercises sessions to Twitter and those users who do not?

To answer this, a between subject *t*-test with the average score on ROPAS items as the dependent variable and the dummy variable for Twitter publications was used to create groups. The results indicated that *users who published their exercise sessions to Twitter have significantly higher ROPAS scores (M = 3.84, SE = 0.10) than the users who don't publish to Twitter;* (M = 3.56, SE = 0.09, t(519) = -2.156, p < 0.05).

RQ14

What part is played by the persuasive design factors in the BCSS scale on the users intention to continue using the system?

To examine the relationships of all of the constructs in the model on *intent to continue,* the scale for CONT is regressed on SOCS, CRED, EFFO, DIAL, EFFE, PRIM and SOID, with results presented in Table 49. All of the constructs have positive relationships with intention to continue using the system that are significant at the 0.05 level of significance except the social constructs, SOCS and SOID, and PRIM. Lehto & Oinas-Kukkonen (2013) suggest a direct effect for SOCS and the same was hypothesized here, however, the significant relationship was not revealed for SOCS in this dataset. In terms of coefficients the largest effect was hold by EFFO and CRED, 0.321 and 0.277, respectively. The result is consistent with the previous research in which, similar to here, *EFFO has the largest direct effect on CONT.* Observe that the relationship between PRIM and intention to continue using the system is significant at only the 0.09 level of significance, but Lehto & Oinas-Kukkonen suggest that PRIM has only an indirect effect on intention to continue through its effects on EFFE and EFFO, which directly influence intention to continue. Qualitatively similar results were obtained in each of the subsamples used for invariance testing.

Table 21. *Regression Estimates for CONT Regressed on SOCS, CRED, EFFO, DIAL, EFFE, PRIM, and SOID*

Scale Averages	Coeff.	Std. Err.	t	P>|t|	95% LCL	95% UCL
SOCS	-0.039	0.060	-0.645	0.519	-0.156	0.079
CRED	0.277	0.080	3.456	0.001	0.120	0.435
EFFO	0.321	0.055	5.868	0.000	0.214	0.429
DIAL	-0.154	0.065	-2.369	0.018	-0.282	-0.026
EFFE	0.120	0.050	2.379	0.018	0.021	0.219
PRIM	0.103	0.061	1.700	0.090	-0.016	0.223
SOID	0.058	0.055	1.052	0.293	-0.051	0.167
Constant	1.596	0.299	5.345	0.000	1.009	2.182

Table 22 depicts results of the regression of ONLINE_ACTIVITY_SUM a variable explained and used in a previous analysis here, on the seven factors in the model as well as ROPAS. From this it can be discerned that the extent to which a user exploits the social networking features of the *movescount*.com system is statistically significantly affected by only the social factors, SOCS ($B = 0.736$, $SE = 0.174$, $p < 0.001$), SOID ($B = 1.116$, $SE = 0.178$, $p < 0.001$), and EFFO ($B = 0.344$, $SE = 0.151$, $p = 0.023$), the effort required to use the system. The remaining factors and ROPAS are not statistically significant at conventional levels.

Table 22. *Regression of the Sum of Five Usage Responses (9e, 9f, 9g, 9h, 9j) aka ONLINE_ACTIVITY_SUM on SOID, SOCS, ROPAS, CRED, EFFO, DIAL, EFFE, PRIM*

Scale Averages	Coeff.	Std. Err.	t	P>|t|	95% LCL	95% UCL
SOID	1.116	0.178	6.259	0.000	0.766	1.467
SOCS	0.736	0.174	4.226	0.000	0.394	1.078
ROPAS	0.066	0.067	0.985	0.325	-0.065	0.197
CRED	-0.681	0.381	-1.788	0.074	-1.430	0.067
EFFO	0.344	0.151	2.273	0.023	0.047	0.642
DIAL	-0.205	0.188	-1.089	0.277	-0.575	0.165
EFFE	0.046	0.121	0.384	0.701	-0.191	0.284
PRIM	-0.140	0.191	-0.732	0.464	-0.514	0.235
Constant	3.615	1.521	2.376	0.018	0.626	6.603

Taken together, Tables 21 and 22 suggest that *the extent to which a user exploits the social features of the movescount.com system do not significantly influence their intention to continue using the system* and the regression of the average response to CONT on the sum of the usage variables indicates that the sum of the usage responses is not statistically significantly associated with an intention to continue using the system. In the structural equation model estimated subsequently, an indirect effect of the social variables is identified that modifies the conclusion presented here.

RQ15
Can we create a structural model that will represent the association between a user's intent to continue using the system, BCSS persuasive systems design factors, key user demographics, exercise usage, online group membership and prior exercise behaviour?

Factor Analysis and the Number of Factors in the Survey

To frame the structural equation model, principal components analysis (PCA) was firstly used to determine the appropriate number of common factors from the survey responses to the BCSS questions. The PCA indicated five components with eigenvalues greater than 1.0. The scree plot for the PCA is provided in Figure 36. Since a component that has an eigenvalue less than 1 will explain no more variance than the average item in the survey, a five-factor model was sought. Observe that the KMO statistic suggests the data suitable for factor analysis (KMO = 0.91, p = 0.000).

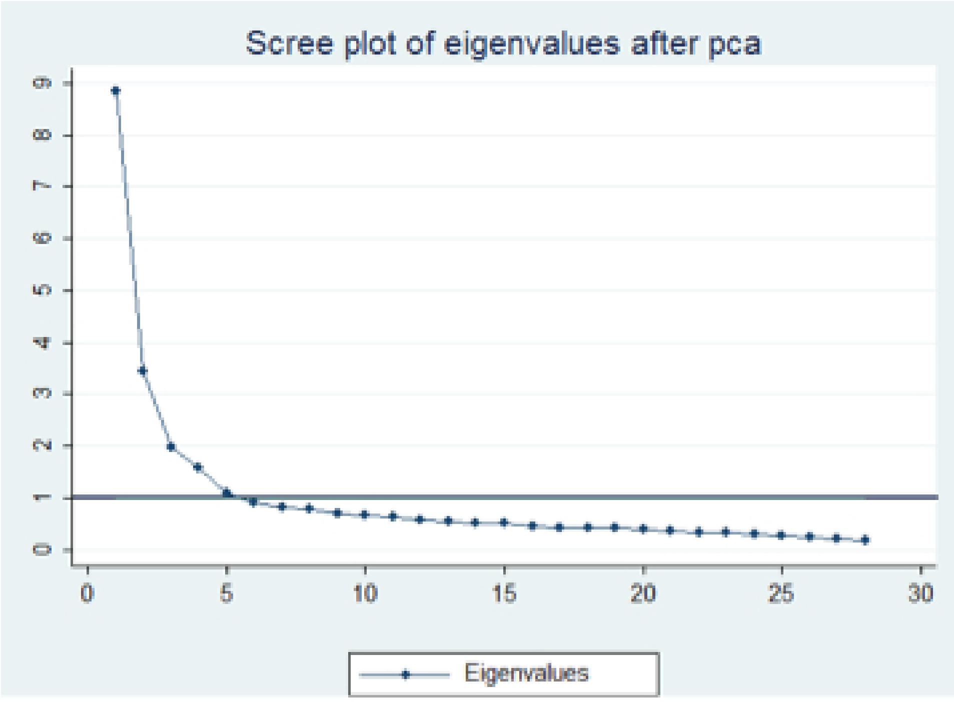

Figure 36. Scree plot of Eigenvalues after PCA of 5 factor BCSS scale.

Based on the principal components analysis, a factor analysis approach that leveraged maximum likelihood to find loadings for five factors was used and the solution was rotated using the *varimax rotation* with the *Kaiser normalization.* Results indicate that the first factor explains 17.35% of the variance, the second factor 13.39% of the variance, the third factor 11.21% of the variance, the fourth factor 6.57% of the variance and the fifth factor 3.51% of the variance as depicted in Table 24. From the factor loadings in this table, item BCSS_j could be loaded on either the first or second factor though the nature of its content is more in line with the items whose largest loadings were on the second factor. The first factor is the same items as were originally labelled as credibility (CRED) by Lehto and Oinas-Kukkonen (2014). These items refer to the user's trust in the system, as discussed briefly above, and this convention was maintained by referring to the factor as **CRED**. The second factor combines all of the items that were included as dialog support (DIAL), primary task support (PRIM), and perceived effectiveness (EFFE). Taken together, *these items refer to the appropriateness of broad design features of the system to the extent that a user finds them helpful in maintaining their exercise regimen* and we will refer to them as **SYSTEM**. The third factor combines all of the items that were referred to as social identity (SOID) and social support (SOCS) by Lehto and Oinas-Kukkonen (2014). These items indicate *whether the user feels a sense of social identity or community with other users and whether the user believes the system provides a means for social support within that community.* We refer to this factor as **SOCIAL**. The fourth factor contains the same items as effort contained in Lehto and Oinas-Kukkonenen (2014). These items indicate how difficult the system is for the user to operate and perform the desired tasks. Again, referring to this factor as **EFFO** follows convention. The fifth factor contains two questions on intention to continue using the system, and we refer to this factor as **CONT**.

Table 23*Varimax-Rotated Factor Loadings of the BCSS Items and Explained Variance of the Five Factors*

	Factors				
	1	2	3	4	5
% of Variance	17.35	13.39	11.21	6.57	3.51
Eigenvalues	4.86	3.75	3.14	1.84	0.98
Items					
bcss_x	**0.84**	0.15	0.04	0.11	0.06
bcss_z	**0.82**	0.21	0.05	0.10	0.13
bcss_n	**0.76**	0.18	0.12	0.09	0.03
bcss_r	**0.76**	0.19	0.11	0.12	0.10
bcss_g	**0.69**	0.16	0.02	0.14	-0.02
bcss_f	**0.64**	0.04	0.08	0.06	0.12
bcss_w	**0.56**	0.27	0.02	0.33	0.07
bcss_k	**0.54**	0.24	0.05	0.31	0.04
bcss_j	0.32	**0.32**	0.05	0.26	0.01
bcss_v	0.13	**0.75**	0.15	0.03	0.17
bcss_y	0.28	**0.72**	0.11	0.14	0.05
bcss_a	0.12	**0.65**	0.18	0.12	0.18
bcss_m	0.28	**0.65**	0.18	0.13	-0.05
bcss_p	0.15	**0.62**	0.26	0.10	0.17
bcss_d	0.07	**0.49**	0.31	0.11	-0.18
bcss_b	0.25	**0.48**	0.10	0.23	0.10
bcss_t	0.17	**0.47**	0.25	0.08	-0.16
bcss_q	0.13	0.10	**0.74**	0.11	-0.03
bcss_c	0.04	0.27	**0.73**	0.02	-0.01
bcss_l	0.10	0.18	**0.71**	-0.05	-0.05
bcss_aa	0.16	0.08	**0.65**	0.12	0.12
bcss_u	0.05	0.24	**0.64**	-0.01	-0.13
bcss_i(reverse)	-0.09	0.11	**0.55**	-0.05	0.14
bcss_o	0.37	0.27	0.07	**0.67**	0.05
bcss_h	0.30	0.15	0.11	**0.65**	0.11
bcss_e(reverse)	0.08	0.12	-0.08	**0.60**	0.31
bcss_s(reverse)	0.12	0.06	-0.03	0.18	**0.56**
bcss_ab	0.35	0.27	0.15	0.29	**0.51**

Table 24 provides summary statistics for scales computed as the simple average of responses from the five-factor solution along with reliability as measured by Cronbach's alpha. Observe the reliabilities ranges from 0.56 (CONT) to 0.90 (CRED), which indicate these constructs are sufficiently reliable to be suitable for analysis. The rationale of treating CONT reliability score (0.54) in acceptable range was described above. The scale is highest for CONT; 92.13% of respondents (480 out of 521) either agreed or strongly agreed with the single item that they intend to continue using the system. The lowest average is for SOCIAL, which is statistically significantly below the "neutral" response of 3 on a five point Likert scale. The remaining factors are all statistically significantly above 3.

In the two subsamples, there were some differences in CFA (confirmatory factor analysis) results. In the measurement model, EFFO determines the response to "using the system is difficult for me" in a significantly significant manner, but there existed a statistically different strength of relationship in the two subsamples. The same is true for SOCIAL and "I consider the other users of the system as my peers". The estimated variances were statistically significantly different for items *aa, v, f, x* and *c* as well as the construct EFFO. Among the covariance estimates in the structural model, only the covariances between SYSTEM and EFFO were significantly different in the two subsamples.

Table 24 *Summary Descriptive Statistics for Scales for the Five Constructs*

Surveys BCSS constructs (5-likert)	Mean	SE	t	p	25th	50th	75th	Cronbach α
SYSTEM_ave	3.60	0.03	20.00	<0.001	3.22	3.67	4.00	0.86
SOCIAL_ave	2.87	0.03	-4.33	<0.001	2.33	3.00	3.50	0.84
CRED_ave	3.99	0.02	49.50	<0.001	3.88	4.00	4.13	0.90
EFFO_ave	4.04	0.03	34.67	<0.001	4.00	4.00	4.33	0.76
CONT_ave	4.36	0.03	45.33	<0.001	4.00	4.50	5.00	0.56

Table 25 provides correlations among the five-factors and O_SOC and ROPAS. As shown in correlations Table 25 for the eight-factor model, all correlations are statistically significant at least the 0.05 level of significance except for O_SOC and EFFO and O_SOC and CRED. The strongest correlations are between CRED and SYSTEM (r = 0.501) and between CRED and EFFO (r = 0.483).

Observe that CRED (r = 0.394) and EFFO (r = 0.452) are the variables most strongly correlated with CONT.

Table 25 *Correlations among scales for 5 BCSS factor, O_SOC and ROPAS*

	CONT	SYSTEM	SOCIAL	EFFO	CRED	ROPAS	O_SOC
CONT	1.000						
SYSTEM	0.325	1.000					
SOCIAL	0.131	0.449	1.000				
EFFO	0.452	0.424	0.129	1.000			
CRED	0.394	0.501	0.204	0.483	1.000		
ROPAS	0.128	0.198	0.335	0.106	0.147	1.000	
O_SOC	0.117	0.094	0.174	0.002	0.049	0.161	1.000

Figures 37 to 43 provide distribution histograms for each of the scales except for CONT, which is positively skewed, and ROPAS, which has a modal value of 1, the distributions are roughly symmetric.

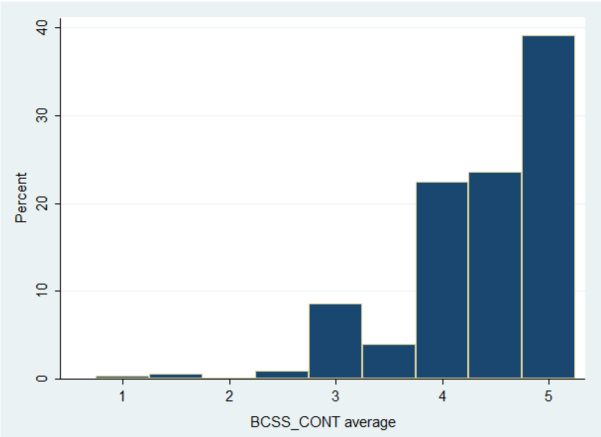

Figure 37. Distribution histogram of BCSS Construct CONT_average.

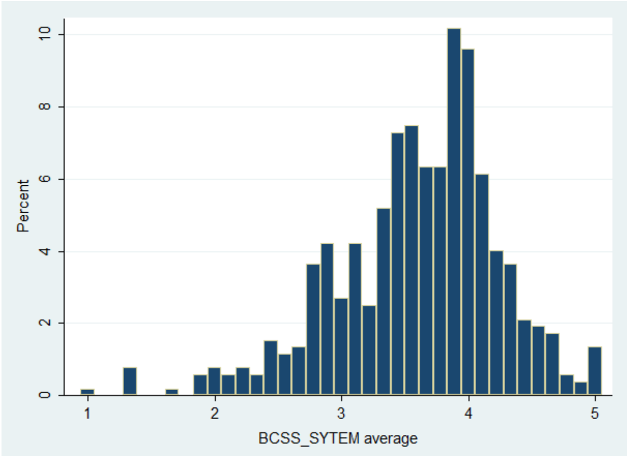

Figure 38. Distribution histogram of BCSS Construct SYSTEM_average.

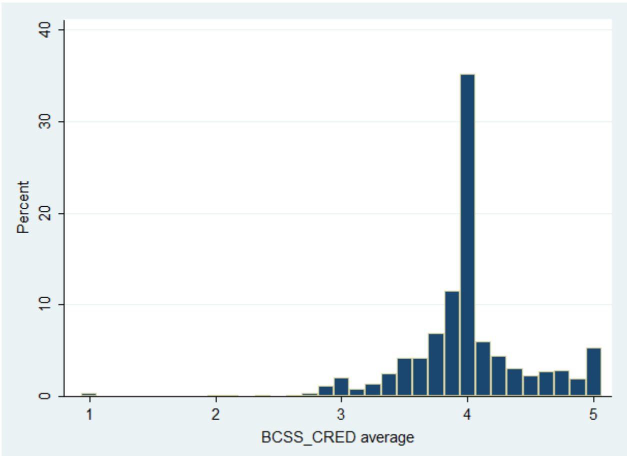

Figure 39. Distribution histogram of BCSS Construct CRED_average.

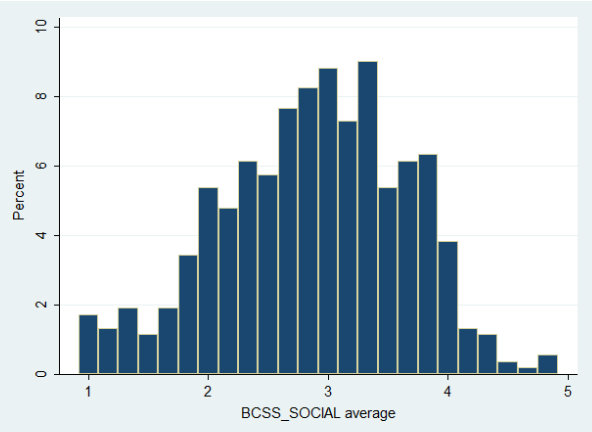

Figure 40. Distribution histogram of BCSS Construct SOCIAL_average.

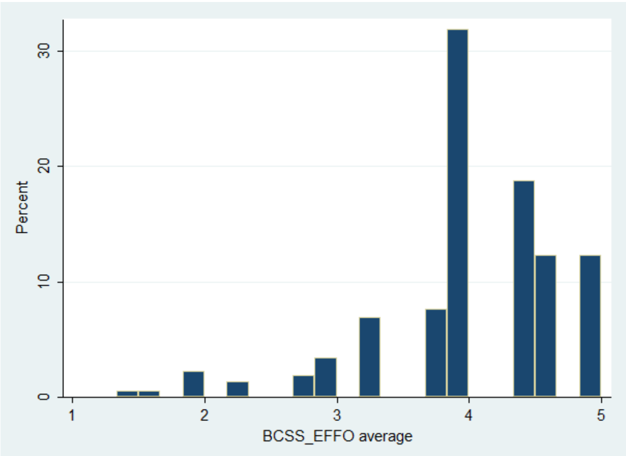

Figure 41. Distribution histogram of BCSS Construct EFFO_average.

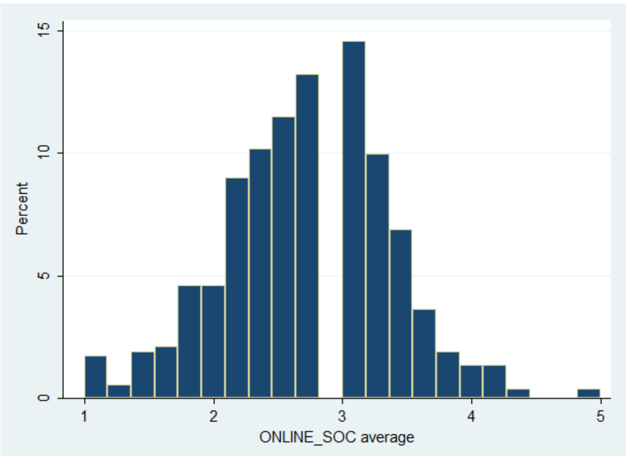

Figure 42. Distribution histogram of BCSS Construct O_SOC_average.

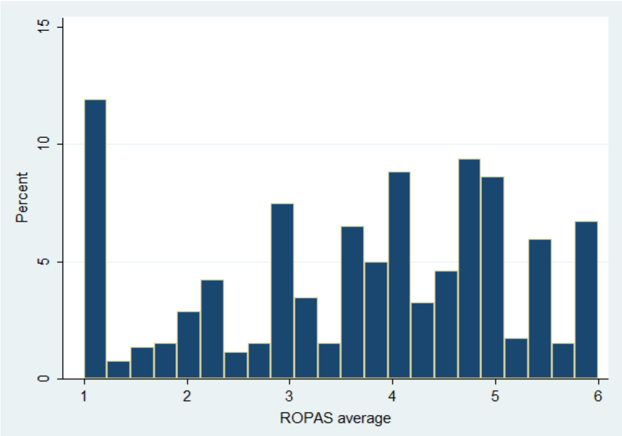

Figure 43. Distribution histogram of ROPAS_average.

Structural Equation Model

Technical considerations

Refer to Appendix I for the rationale behind the selection of the SEM method used to explain the associations between a user's intent to continue using the system, the design of the system itself, age and marital status of the user and their exercise volume as uploaded to the system. This consideration explores the fundamental principles of SEM and its relevance to the problem specified in RQ 15.

Structural Equation Model Specifications

Table 23 presented in the last section lists the variables for the items for the five factors that originate from the BCSS questionnaire defining the part of the measurement model that is related to BCSS items. An explanation of the derivations and meanings for each of the five factors used in the survey is provided earlier.

For example, factor 1 in Table 23, which is referred to as CRED, is measured by the items bcss_x, bcss_z, bcss_n, bcss_r, bcss_g, bcss_w, and bcss_k.. The measurement model for factors 2 through 5 in Table 23 (namely, the constructs SYSTEM, SOCIAL, EFFO and CONT, respectively) can be found similarly. The remaining parts of the measurement model consist of measures for ROPAS and O_SOC, and these constructs are each measured by their respective items. Parameter estimates are not discussed from the measurement model produced here.

Path Diagram

Figure 44below provides **a path diagram** to define relationships amongst the latent variables along with the observed exogenous variables that have been included in the model. Starting from the left hand side, ROPAS is hypothesized to be a function of age and marital status. Additionally, it has been assumed that an indicator variable is defined to be 1 if the respondent joined a group and named as Joined_Group; Joined_Group is related to O_SOC.

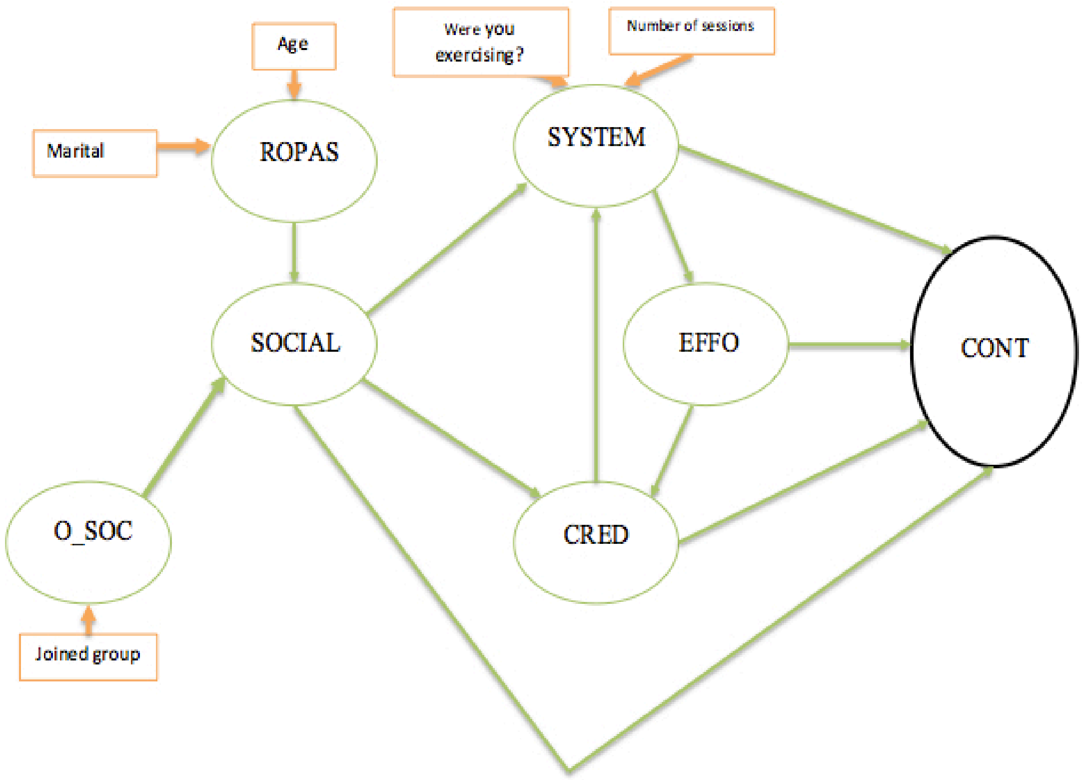

Figure 44. PATH diagram for structural model – use continuance for an exercise tracking system

Because ROPAS indicates the extent to which a respondent engages with others during exercise and O_SOC indicates their use of the Internet for social purposes, it seems natural to suppose that ROPAS and O_SOC will influence SOCIAL. SOCIAL, in turn, affects three other variables. Firstly, high values of SOCIAL should be associated with high regard for system features as reflected in SYSTEM, since the social aspect of the system (e.g., being able to shout and post thumbs) is a key component of the system. Second, SOCIAL is among the determinants of CRED since some aspects of credibility, such as trust and reliability, are also criteria by which the social features of the system are evaluated. Finally, SOCIAL is hypothesized to affect CONT, since engagement through the social aspects if the device should lead to continued use of the device.

In addition to SOCIAL, SYSTEM is also determined by CRED, which reflects the previous literature to the extent that a system that is rated as credible is likely to be well regarded. SYSTEM also has two observed exogenous variables. Posting an exercise session or move to the system can be taken as an indicator of high regard for the system, so that number of exercise sessions posted is hypothesized to be positively related to SYSTEM. The indicator variable **Were You Exercising Previously**, which has a value of 1 for exercise within a year prior to purchasing the device is included because this defines a group of people who chose to exercise independently of the device, and it is important to understand their response to the system and whether it differs from people who were enticed either to exercise for the first time or are restarting a moribund exercise regime through the system. SYSTEM affects two other variables, EFFO and CONT for fairly straightforward reasons. EFFO, the effort required to use the system, is determined only by SYSTEM, but determines CRED as well as CONT. Since CRED also affects SYSTEM, there is a feedback loop from SYSTEM through EFFO through CRED by which the device can generate its own credibility through design features that are well-suited to task support and easy to use.

The relations defined by the measurement model for ROPAS, O_SOC, and the BCSS items and the path diagram given in Figure 42 provide the equations that are used to estimate the model. All that remains is to specify an assumed probability distribution for variables. A commonly used assumption is that the latent variables and all observable variables are jointly normally distributed. However, as described above, several of our observable variables are dichotomous indicators and therefore cannot be assumed to be a part of a joint normal distribution because they can take on only two values whereas the normal distribution ranges over the whole real line. For this reason, it is assumed that the distribution of the error term in each equation that is conditional on the observable variables in the equation follows a normal distribution.

Model Estimates

Table 27 provides estimated coefficients for the model along with standard errors, *z* statistics, *p* values and confidence intervals. Before discussing the estimates, several indicators of model adequacy are assessed.

First the feedback between CRED, EFFO and SYSTEM is **stable**. In an unstable system, parameter estimates imply dynamic behavior to the extent that the value of one or more of these variables would be unbounded, as for example, each additional unit of CRED triggered an additional unit of SYSTEM, which caused an additional unit of CRED and so on. In this instant, the feedback between CRED, SYSTEM and EFFO would lead all of these variables to converge to finite values.

Second adequacy indicator, for each equation in the system, the null hypothesis that all coefficients are equal to zero can be rejected using a Wald test; all *p* values for these Wald tests are less than 0.01. Thirdly, Table 26 lists goodness of fit statistics, R squared for each of the observed endogenous variables (that is, the measures for each factor) and the latent endogenous variables. It is clear from this table that fits for ROPAS and O_SOC are not especially strong, but the remaining endogenous variables have stronger R squares ranging from 0.15 to 0.46. Overall, the model has an R square of 0.21.

Table 26 *R squared values for the model*

Construct for items	Observed Variables	R^2	Construct for items	Observed variables	R^2	Construct for items	Observed variables	R^2
CONT	bcss_ab	0.95	CRED	bcss_x	0.73	ROPAS	ropas_a	
	r_bcss_s	0.18		bcss_z	0.73		ropas_b	
SYSTEM	bcss_j	0.20		bcss_n	0.61		ropas_c	
	bcss_v	0.56		bcss_r	0.64		ropas_d	0.84
	bcss_y	0.63		bcss_g	0.51		ropas_e	0.82
	bcss_a	0.48		bcss_f	0.40		ropas_f	0.82
	bcss_m	0.55		bcss_w	0.45		CONT	0.39
	bcss_p	0.49		bcss_k	0.41		EFFO	0.28
	bcss_d	0.29	EFFO	r_bcss_e	0.33	Latent variables	CRED	0.36
	bcss_b	0.37		bcss_h	0.55		SOCIAL	0.15
	bcss_t	0.28		bcss_o	0.71		SYSTEM	0.46
SOCIAL	bcss_q	0.56		o_soc_a	0.16		O_SOC	0.02
	bcss_c	0.61		o_soc_b	0.42		ROPAS	0.03
	bcss_l	0.53		o_soc_c	0.47		Overall	0.21
	bcss_aa	0.43		o_soc_d	0.13			
	bcss_u	0.45		o_soc_e	0.20			
	r_bcss_i	0.29		bcss_h	0.55			
	bcss_v	0.56		bcss_r	0.64		ropas_d	0.84
	bcss_y	0.63		bcss_g	0.51		ropas_e	0.82
	bcss_a	0.48		bcss_f	0.40		ropas_f	0.82
	bcss_m	0.55		bcss_w	0.45		CONT	0.39
				bcss_k	0.41		EFFO	0.28

Model Fit

Overall model fit can be assessed in several ways. The traditional criterion is a chi-squared test of the null hypothesis that the structural model fits observed covariances as well as the saturated model, where the saturated model is just the sample of estimates of the covariances. For this estimation, the chi-square statistic for the model versus the saturated model is 2,223 with 881 d.f., which leads to a p value < 0.001. However, for models with this number of observations, it is not uncommon to reject the null hypothesis with a reasonably good fit.

Browne & Cudeck (1996) and (Rigdon, 1996) suggest that a root mean squared error of approximation (RMSEA) for the covariance matrix of 0.05 or less is a good fit and that the standardized root mean squared error (SRMR) should be less than 0.08. The RMSEA for our model is 0.054, and the SRMR is 0.059. Additionally, the Comparative Fit Index (CFI) for our model is 0.881 and the Tucker-Lewis Index (TLI) is 0.874. Values of 0.90 are frequently used as cutoffs for a good fit for these indices. However, (Hu & Bentler, 1998) indicate that a CFI and TLI may be less useful measures of goodness of fit in the opresence of low RMSEA values such as 0.05. Overall, the model has an accpetable fit.

Estimates for the model are presented in Table 27. Starting with CONT, intention to continue, all of the other variables in the model have the anticipated positive signs, and EFFO, CRED and SYSTEM are signficant at less than the 0.05 level of signficiance. Standardized coefficient scores indicating a moderate effect for all of the constructs (r = 0.410, r = 0.295, r = 0.341, respectively). However, SOCIAL is not statistically signficiantly different than zero. For EFFO, SYSTEM has the anticipated sign (large effect size, r = 0.580) and the null hypothesis that the coefficient is equal to zero can be overwhelmingly rejected. For CRED, both SOCIAL and EFFO have the anticipated positive signs and each is signficiant at less than the 0.05 level of signficiance. EFFO has a moderate effect size (r = 0.460), whereas the coefficient of SOCIAL construct indicates a small effect size.

Table 27 *Estimated Coefficients for the Structural Model*

	Standardized Coefficient	Robust Std. Err.	z	P>|z|	95% LCL	95% UCL
CONT						
EFFO	0.311	0.117	2.660	0.008	0.082	0.540
CRED	0.215	0.074	2.910	0.004	0.070	0.360
SOCIAL	0.039	0.064	0.620	0.536	-0.085	0.164
SYSTEM	0.191	0.088	2.180	0.029	0.019	0.363
EFFO						
SYSTEM	0.427	0.063	6.820	0.000	0.305	0.550
CRED						
EFFO	0.477	0.054	8.770	0.000	0.371	0.584
SOCIAL	0.140	0.050	2.830	0.005	0.043	0.238
SOCIAL						
O_SOC	0.187	0.071	2.650	0.008	0.049	0.326
ROPAS	0.343	0.047	7.270	0.000	0.251	0.436
SYSTEM						
CRED	0.315	0.054	5.790	0.000	0.208	0.421
SOCIAL	0.431	0.042	10.300	0.000	0.349	0.513
Exercised before	-0.106	0.039	-2.730	0.006	-0.182	-0.030
Number of sessions	0.142	0.033	4.310	0.000	0.078	0.207
O_SOC						
Joined Group	0.155	0.062	2.510	0.012	0.034	0.276
ROPAS						
Age	-0.169	0.047	-3.580	0.000	-0.262	-0.077
Marital status	-0.104	0.049	-2.110	0.035	-0.201	-0.007

For the SYSTEM equation, CRED and SOCIAL are both positively related to respondent’s views about the appropriateness and usability of the system, and each is signficiant at the 0.05 level of signficance and have moderate effect sizes (r = 0.241 and r = 0.236, respectively). *A history of exercise within the previous year lower’s a respondent’s view of the system by a statistically signficant amount*. However, as could be expected, users assessment of the system increases with the number of exercise sessions they have uploaded, implying that their behavior in uploading systems reflects a positive view of the system. Given the positive and significant coefficients from CRED to SYSTEM, SYTEM to EFFO, and EFFO to CRED, it may be possible for the exercise device to develop credibility through design features that reduce the effort in using the system. The magnitude of this effect is explored.

As hypothesiszed, SOCIAL is significantly positively affected by ROPAS and O_SOC. *Joining a group online is an indicator for a statistically signficantly higher value of O_SOC,. Increases in age and being single statistically signficantly lower ROPAS.*

Total Effects for the Model

Table 28 provides estimates of the total effects of the model. Total effects are the sum of direct and indirect effects. Total effects can reveal the subtle effects of variables working through other variables. For example, it indicates that SOCIAL does not have a direct effect on the intention to continue using the system. However, the total effect of SOCIAL on CONT, 0.251, is different than zero at a significance level of less than 0.001 because SOCIAL raises SYSTEM and CRED and SYSTEM and CRED have significant effects on intention to continue. The variable with the largest effect on intention to continue is SYSTEM, 0.703, even though it has a smaller direct effect than EFFO, because SYSTEM has a positive effect on EFFO and EFFO has a large direct effect on CONT. Summarizing, for intention to continue using the system (CONT), SYSTEM and EFFO has the largest effects ($r = 0.703$ and $r = 0.624$), CRED and SOC has moderate effects ($r = 0.464$ and $r = 0.251$), and all others (O_SOC, ROPAS, Exercising before, number of sessions, and age) have very small effects (all coefficients is less than 0.100).

Table 28 *Total effects*

	Standardized coefficient	Robust std. err.	z	P>|z|	95% LCL	95% UCL
CONT						
EFFO	0.624	0.123	5.080	0.000	0.383	0.864
CRED	0.464	0.109	4.240	0.000	0.250	0.679
SOCIAL	0.251	0.065	3.850	0.000	0.123	0.379
SYSTEM	0.703	0.166	4.230	0.000	0.377	1.029
O_SOC	0.079	0.036	2.210	0.027	0.009	0.148
ROPAS	0.044	0.006	6.760	0.000	0.031	0.056
Exercising before	-0.085	0.033	-2.560	0.011	-0.150	-0.020
Number of sessions	0.003	0.001	3.190	0.001	0.001	0.004
Age	-0.001	0.000	-2.560	0.011	-0.002	0.000
Marital status	-0.015	0.008	-1.830	0.068	-0.032	0.001
Joined Group	0.012	0.008	1.480	0.139	-0.004	0.027
EFFO						
EFFO	0.069	0.015	4.530	0.000	0.039	0.098
CRED	0.149	0.035	4.290	0.000	0.081	0.218
SOCIAL	0.161	0.025	6.480	0.000	0.113	0.210
SYSTEM	0.620	0.123	5.030	0.000	0.378	0.861
ONLINE_SOC	0.050	0.023	2.210	0.027	0.006	0.095
ROPAS	0.028	0.004	6.760	0.000	0.020	0.036
Exercising before	-0.075	0.029	-2.600	0.009	-0.131	-0.019
Number of sessions	0.002	0.001	3.380	0.001	0.001	0.004
Age	-0.001	0.000	-2.690	0.007	-0.001	0.000
Marital status	-0.010	0.005	-1.850	0.065	-0.020	0.001
Joined Group	0.007	0.005	1.490	0.136	-0.002	0.017
CRED						
EFFO	0.491	0.108	4.530	0.000	0.279	0.704
CRED	0.069	0.016	4.290	0.000	0.037	0.100
SOCIAL	0.175	0.042	4.180	0.000	0.093	0.257
SYSTEM	0.285	0.057	5.030	0.000	0.174	0.396
ONLINE_SOC	0.055	0.025	2.210	0.027	0.006	0.103
ROPAS	0.030	0.004	6.760	0.000	0.022	0.039
Exercising before	-0.034	0.014	-2.390	0.017	-0.063	-0.006
Number of sessions	0.001	0.000	3.140	0.002	0.000	0.002
Age	-0.001	0.000	-2.560	0.011	-0.001	0.000
Marital status	-0.011	0.006	-1.870	0.062	-0.022	0.001
Joined Group	0.008	0.005	1.490	0.137	-0.003	0.019
SOCIAL						
ONLINE_SOC	0.313	0.141	2.210	0.027	0.036	0.590
ROPAS	0.174	0.026	6.760	0.000	0.124	0.224
Age	-0.004	0.001	-3.070	0.002	-0.007	-0.002
Marital status	-0.061	0.030	-2.010	0.045	-0.120	-0.001
Joined Group	0.046	0.030	1.550	0.120	-0.012	0.105

	Standardized coefficient	Robust std. err.	z	P>|z|	95% LCL	95% UCL
SYSTEM						
EFFO	0.118	0.026	4.530	0.000	0.067	0.170
CRED	0.258	0.060	4.290	0.000	0.140	0.375
SOCIAL	0.278	0.043	6.480	0.000	0.194	0.363
SYSTEM	0.069	0.014	5.030	0.000	0.042	0.095
ONLINE_SOC	0.087	0.039	2.210	0.027	0.010	0.164
ROPAS	0.048	0.007	6.760	0.000	0.034	0.062
Exercising before	-0.129	0.047	-2.750	0.006	-0.221	-0.037
Number of sessions	0.004	0.001	3.780	0.000	0.002	0.006
Age	-0.001	0.000	-2.760	0.006	-0.002	0.000
Marital status	-0.017	0.009	-1.890	0.059	-0.034	0.001
Joined Group	0.013	0.008	1.550	0.122	-0.003	0.029
O_SOC						
Joined Group	0.148	0.057	2.600	0.009	0.036	0.260
ROPAS						
Age	-0.025	0.007	-3.550	0.000	-0.039	-0.011
Marital status	-0.348	0.166	-2.100	0.036	-0.673	-0.024

For the subsamples used to test the invariance of the structural equation model, there were no differences that were significant at the 0.05 level of significance in the structural equations. For the measurement model, the subsamples had statistically significantly different coefficients for O_SOC.

Summary of Findings

RQ8

What portion of the sample population was actively exercising prior to purchasing the Suunto device and system?

More than 85 percent of the sample (445/521) had exercised in the year preceding their purchase of the device. Of the 75 people who had not exercised in the year prior to purchasing the device, 80 percent had exercised at some point in their lives.

RQ9

How regularly did users indicate they used the device as part of their normal exercise regime?

At least 75 percent of the respondents reported regularly wearing the device, logging into the system and uploading an exercise session (move).

RQ10

What were the most popular functions of the movescount.com system in the sample?

Of the possible uses of the device, the most popular when ranked by the mean is following another user, followed by joining a group.

RQ11

Does analysis of the movescount.com sample population responses to the BCSS scale reveal consistency with the existing evidence?

Initial validation of the data showed all of these (BCSS scale) factors had a reliability value acceptable for analysis of relationships using these constructs. All of the constructs or factors have significant correlations except O_SOC and DIAL, O_SOC and EFFO and O_SOC and CRED. Observe that there are especially strong correlations between SOCS and SOID (0.745), PRIM and EFFE (0.625) and PRIM and DIAL (0.641) and DIAL and EFFE (0.592). PRIM and CRED are also correlated at more than the 0.5 level. From the survey data, effectiveness (EFFE) is strongly correlated with primary task support (PRIM), dialog support (DIAL) and effort (EFFO). Overall, this was very consistent with previous studies and the exception shown by the O__SOC factor that was introduced by the current study, being an external standardised subscale for assessing the online sociability of users. As well, the same positive relationship between PRIM and EFFE and PRIM and EFFO was evident in the movescount.com population sample among the latent constructs in their structural equation models as was found by earlier authors. Existing literature shows that the perceived social support (SOCS) provided by the system also entices users to continue using the system. In turn, perceived social support is determined by dialog support (DIAL) the system provides and the extent to which it cultivates identification among users as a group with shared characteristics and goals (SOID). Analysis from the current study uncovered similar positive correlations.

RQ12

Does an individual's ROPAS score in any way predict the perceived Social Support and Social Identification functions of the system?

ROPAS results do predict SOCS scores although SOID fully mediates the relationship between ROPAS and SOCS scores.

RQ13

Is there a difference in the ROPAS scores between users who publish exercises sessions to Twitter and those users who do not?

The results indicated that users who published their exercise sessions to Twitter have significantly higher ROPAS scores (*sample mean* = 3.84, *SE* = 0.10) than the users who don't publish to Twitter (*sample mean* = 3.56, *SE* = 0.09).

RQ14

What part is played by the persuasive design factors in the BCSS scale on the users intention to continue using the system?

All of the constructs have positive relationships with intention to continue using the system that are significant at the 0.10 level of significance except the social constructs, SOCS and SOID. Lehto & Oinas-Kukkonen (2013) suggest a direct effect for SOCS and the same was hypothesized here, however, the significant relationship was not revealed for SOCS in this dataset. In terms of coefficients the largest effect was shown by EFFO and CRED, with 0.321 and 0.277, respectively.

RQ15

Can we create a structural model that will represent the association between a user's intent to continue using the system; BCSS persuasive systems design factors, key user demographics, exercise usage, online group membership and prior exercise behaviour?

A compete model was generated being estimated on the five BCSS constructs SOCIAL, SYSTEM, CRED, EFFO, CONT and the two additional constructs ROPAS and O_SOC. The path diagram in Figure 49 illustrates the nature of relationships amongst the latent variables and the observed exogenous variables that were included in the model; these exogenous variables included Age, Marital Status, Whether or not a User Joined an Online Group, A User's Exercise Status Prior to Using the System and Number of Exercise Sessions. It revealed many relationships consistent with those that appear in the previous BCSS literature. For example we find that SYSTEM, CRED and EFFO are all positively associated with intention to continue using the device. In contrast to the previous literature but consistent with our regression analysis, SOCIAL does not affect intention to continue using directly, but does have a substantial and statistically significant indirect effect through its direct effects on SYSTEM and CRED. The interpretation could be that the social features of the system have been implemented in a way that creates a sense of trust, reliability, and appreciation of system design along with dialog support that leads to increased intention to continue using, even if the social features themselves would not cause an increased intention to use. It was also found that ROPAS and O_SOC are significantly positively related to SOCIAL, and that the total effects of demographic variables that influence O_SOC or ROPAS have total effects on intention to continue using that are attenuated by more important user perceptions of attributes of the system.

Discussion

The findings documented in this chapter along with looking to answer the specific research questions raised, may be the first to shed light, in a small way, on the link between exercise behaviour in the real world and online social interactions in exercise device communities. Applying the ROPAS scale with the BCSS constructs may represent an example of a reasonable means to better understand and measure the association between the established health behaviour change model, SDT in particular its mini-theory BPNT and how people use activity tracking systems to commence or maintain exercise behaviour. As there are similar scales for measuring other BPNT needs including autonomy (as well as autonomy support) and perceived competence (for exercise and technology use), it is feasible that users of various exercise tracking systems can have their needs satisfaction measured in conjunction with assessment of the persuasive efficacy of the system by using similar analytic techniques employed in Study Two of this thesis. Perhaps better understanding needs satisfaction and gaining a measure of an individual user's motivational state can aid systems designers to better align the design of the system to more effectively persuade and support the user in meeting behavioural goals that match their motivational state.

One aim of the study was to determine if the system met the goals of a BCSS or persuasive system as outlined by Oinas-Kukkonen (2013), namely, altering a behavior, forming a behavior, and or maintaining a behavior. *In terms of exercise,* *forming the behavior and then maintaining or even strengthening that behavior are likely the more relevant behaviours witnessed in the study sample* rather than altering a behavior. In the sample, only 80 of 521 respondents had not exercised in the year prior to acquiring the device, and only 15 of these 80 had never exercised before. Practically then the study focus has been on users who are either maintaining or possibly strengthening their exercise behaviour. Realistically, *the number of users who exhibited commencing exercise behaviour for the first time was found to be too small to analyse meaningfully as a group.*

In the structural equation model, the variable "*were you exercising before" has a direct effect in lowering a user's perception of the overall features of the system*. As a result these users displayed somewhat less positive perceptions of the effort needed to use the system, its overall credibility and a somewhat lower intention to continue using the system. Perhaps this reflects a level of expectation dissonance from the users. Suunto, like its competitors expends enormous effort and financial investment to entice buyers on the back of a degree of hyperbole concerning the systems functions and benefits, (Oliver, 2010). However, it’s important to note that a chi-square test of whether a user intends to continue or not based on whether they were exercising in the previous 12 months indicates that these two variables are independent. This means we need to view the difference in perceptions of people who have been exercising versus people who have not been exercising as perhaps reflective of the system's success in helping achieve the goal of changing behavior or changing an initially out of shape person into a fairly fit person rather than the less exciting success of helping to maintain a behaviour.

A second primary aim of the research was to determine the effects that the social features of the *movescount* system had on the users’ perceptions of the system and their exercise behaviour. The effects of the social components act with subtlety for what seems like a number of reasons. Firstly, the data shows the two constructs of social support (SOCS) and social identification (SOID), as well as the three constructs dialog support (DIAL), primary task support (PRIM) and effectiveness (EFFE) that were features of studies by Lehto, Oinas-Kukkonen and Drozd (2012) and Lehto and Oinas-Kukkonen (2014) are so highly correlated that they appear to be caused by the same underlying factor. Additionally, an original goal was to tie the data from exercise sessions to social use, but the data from the user sample revealed a conflict between what their recorded usage of the system and their reflected interpretation of how they use the system. The result was the analyses generally did not find the social data from the exercise session data collected in Study One to be very useful as predictors in the survey data.

Because the eight-factor solution for the BCSS is internally consistent, its factors could be used along similar lines to that discussed in the existing literature. This established internal consistency enabled the use of ordinary least squares regression analyses that made use of scales that represent the simple averages of item responses for those items that comprise each factor, as observable variables. In the regression models, the social support and social identification factors are not related to intention to continue using the system. A new finding that rose from the regression of the scale variables is that the effect of relatedness to others in physical activity (ROPAS) is mediated by social identification with the system. In other words, a user's high score for the desire to be social in exercise predicts high values of social identification in the system, which in turn predict satisfaction with social support received from the system in such a way that if both ROPAS and SOID are included in the same regression with SOCS as the dependent variable, ROPAS appears to have no effect.

Driven by the subtleties shown in the measures of social association and system-related activity, a closer examination of users was done to identify those people who had no social media accounts when their movescount.com profile was created but use at least one of the social networking functions of the movescount.com site regularly; a grouping referred to as **Unexpected Users**. They were contrasted with measures of those respondents who had at least one social media account at the time their profile was created, but did not tend to use the social networking functions associated with movescount.com; a grouping referred to as **Unexpected Non-Users**. With comparatively higher scores in ROPAS, SOCS and SOCID, it seems that **Unexpected Users** are people who feel part of the *movescount.com* community and receive social support from that community although they use external mainstream online social networks infrequently. There are inconclusive signs that these users may be fitter than their peers.

Chapter 6

Introduction

The theoretical frameworks evolving to assist researchers better understand and direct persuasive systems development are in a nascent state. The gathering of evidence and harnessing of the appropriate behavioural health, software engineering and data analytics skillsets to drive the maturation process required for theories such as BCSS to be used more extensively is a process that is only just gaining momentum. To tap into this small knowledge base was seen as an investigative aid to help us better understand, from a specialist's dispassionate view, exactly how well or otherwise the movescount.com system delivers on the Persuasive Systems Design (PSD) elements essential to the BCSS requirements of persuasive systems. A small panel of experts was convened to deliver on these views.

The analytic processes applied to the panel of experts surveyed in this study looked to satisfy the thesis goal and answer its research question as follows.

Goal Five

To galvanize expert assessments of the level of PSD compliance in the *movescount* app.

Research question

RQ. 16 How completely and effectively does the *movescount.com* system implement the recommended BCSS-PSD design techniques?

Method

To conduct a satisfactory expert analysis of the *movescount.*com web-based system, use was made of a subjective design assessment format as used by Oinas-Kukkonen and Harjumaa (2009) in a study of the analysis of BCSS-PSD design features implemented by web sites. Table 29 shows the items that are ranked by this format on a four point 0 through 3-scale arranged by domain. Each of these items was rated by five different raters on a 4 point scale using the integers 0-3, where 3 is high support, 2 is medium support, 1 is low support and 0 is no support.

Table 29 BCSS-PSD Design Features Used for Expert Rating of movescount.com

System principles	Definition or Principle
Primary task support	
Reduction	Reducing complicated behavior to simpler tasks
Tunneling	Using the system to guide users through behavioral steps
Tailoring	Adapting the system to “needs, interests, personality, usage context, or other factors relevant to a user group”
Personalization	Personalized content may be more persuasive
Self-monitoring	Keeping track of goals supports user’s achievement of them
Simulation	Simulation can show users the connection between causes and effects
Rehearsal	Provides a means for practicing a new behavior
Dialog support	
Praise	Praise makes users more receptive to communication
Rewards	Rewarding targeted behaviors reinforces those behaviors
Reminders	Suggestion of behavior reminds user to perform behavior
Suggestion	Well-adapted suggestions may encourage behavior
Similarity	Finding a similarity with the user may be persuasive
Liking	Systems that are visually appealing may be more persuasive
Social role	If a system has a persuasive role, users may use it for persuasion
Credibility support	
Trustworthiness	Trust enables persuasion
Expertise	Perception of expertise increases persuasive power
Surface credibility	First impressions matter
Real-world feel	Credibility is enhanced by featuring people or real world content
Authority	Use of authority can enhance persuasive power
Third-party endorsements	Third party endorsements from trusted sources increase credibility
Verifiability	Easily verifiable material raises credibility
Social support	
Social learning	Motivation by observing others performing the task
Social comparison	Motivation by permitting comparison of performance
Normative influence	Leveraging peer pressure to influence behavior
Social facilitation	Motivation by performing a task with others
Cooperation	Motivation by tapping into tendency to cooperate
Competition	Motivation by tapping into competitive drive
Recognition	Motivation via public recognition

Ratings are inherently subjective. Different raters bring different experiences to bear, with different standards and will respond differently to the same objective system features. It is unrealistic to consider that a consensus should eventuate across all the system design features listed in Table 29, although some amount of inter-rater agreement is a prerequisite for taking expert opinion as genuinely indicative of strengths and weaknesses of the device. One measure of inter-rater agreement that is useful in this context is Fleiss' kappa (Fleiss, Levin, & Paik, 2003), which measures the difference between the amount of agreement among the raters (expressed as a proportion that they agree on) from the amount of agreement that can be expected as the result of random chance given the proportion of responses in each level of rating. A standardized version of the kappa statistic follows a standard normal distribution and can be used to test the null hypothesis that the raters agree on a proportion of ratings equal to the proportion expected by random chance against the one-sided alternative that the raters agree on a greater proportion of ratings than would be expected by random chance. Consequently, use has been made of Fleiss' kappa statistic to measure inter-rater agreement so that a reliable set of ratings can be derived, either by combination of the ratings scale or by elimination of a rater with outlier assessments

The methods used are organised such that we first explore the reliability of the experts' ratings using the kappa statistics, examine these ratings and any associations in more detail and link these approaches in the results. It was important to seek a rating scale that is reliable, although we do report ratings for each domain of the scale regardless of reliability.

Results

Determination of Raters and their Ratings

Table 30 provides kappa statistics for each point on the scale as well as an overall kappa. The overall kappa figure suggests that there is 21% more agreement among the raters than could be expected because of random chance, which is a statistically significantly different compared to a random level of agreement at less than the 0.0001 level of significance. However, within the scale, there is not a statistically significantly better than random agreement between the two intermediate levels of support, medium and low support, with each generating only 5% more agreement than could be expected from random chance. Clearly, the raters that were polled do tend to agree at the extremes, as the rating of no support and high support garner about 27% and 43% more agreement than could be expected by random chance. The result that intermediate scores have agreement that is statistically insignificantly better than random chance holds as well for the primary task support and dialog support domains of their design principles. For credibility support and social support, only the highest rating has statistically significantly more agreement than would occur by random chance

Table 30 *Kappa statistics for the five panel experts*

Outcome	Kappa	Z	Prob>Z
No support	0.268	4.48	<0.001
Low support	0.048	0.81	0.209
Medium support	0.048	0.81	0.209
High Support	0.429	7.18	<0.0001
Combined	0.210	5.99	<0.0001

Because there is not better than random agreement at the two intermediate levels, reporting results at that level of difference is more than likely unwarranted. There are two options for increasing agreement. One possibility is removing a panellist who seems well “out of line” with their fellow panellists. Table 31 shows the Spearman correlations among the different raters for all of the BCSS-PSD design principles. All of the correlations are statistically significantly greater than zero except for the correlation between panellist-rater 4 and panellist 2, with panellist 2 generally having higher correlations than panellist 4 has with other raters. However, if the ratings of panellist 4 are removed and kappa is re-calculated, the problem of not significantly better than random agreement on the intermediate ratings remains (not shown in a table).

Table 31 *Spearman correlation coefficients amongst panel experts*

	Author	eHealth 1	eHealth 2	eHealth 3	eHealth 4
Author	1.000				
eHealth 1	0.729***	1.000			
eHealth 2	0.743***	0.677***	1.000		
eHealth 3	0.472*	0.365	0.575***	1.000	
eHealth 4	0.594***	0.418*	0.308	0.449*	1.000

*Note: *p < 0.05, **p < 0.01, ***p < 0.001*

The second option is to combine the two intermediate ratings, medium and low support, into one category. Table 32 shows the kappa statistic that results from combining these two categories. For the three possible ratings that are available when the two intermediate options are merged into one option, low/medium support, the kappa statistics indicate significantly better than chance agreement on each category.

Table 32 *Kappa statistics for the five panel experts with a 3-item rating*

Outcome	Kappa	Z	Prob>Z
No support	0.268	4.48	<0.0001
Low/medium support	0.169	2.82	0.002
High support	0.429	7.18	>0.0001
Combined	0.287	6.52	<0.0001

Table 33 indicates variation in the reliability of ratings across the BCSS-PSD Design Categories from Table 33 by providing kappa statistics for each. For **Primary Task Support**, each of the three ratings as well as the overall set of ratings show statistically significantly more agreement than can be expected from random chance. However, **Dialog Support** has no more agreement on the intermediate rating than would be expected by chance and **Credibility Support** has no more agreement on the lowest two ratings than would be expected by chance. For **Social Support**, the entire set of ratings does not exhibit more agreement than would be expected by chance, although the high support rating shows significantly more agreement than chance. The next section provides ratings for each question and design category, but the reliability results of Table 33 should be kept in mind when interpreting ratings.

Table 33 *Kappa Statistics by BCSS-PSD Design Category*

Outcome	Kappa	Z	Prob>Z
Primary task support			
No support	0.497	4.16	<0.0001
Low/medium support	0.309	2.59	0.005
High support	0.572	4.78	<0.0001
Combined	0.450	5.08	<0.0001
Dialog support			
No support	0.205	1.71	0.0435
Low/medium support	0.125	1.05	0.148
High support	0.477	3.99	<0.0001
Combined	0.254	2.98	0.001
Credibility support			

No support	0.028	0.23	0.408
Low/medium support	0.085	0.71	0.239
High support	0.440	3.68	0.0001
Combined	0.184	2.13	0.016
Social support			
No support	-0.029	-0.25	0.597
Low/medium support	0.142	1.19	0.117
High support	0.194	1.62	0.052
Combined	0.158	1.43	0.077
Primary task support			
No support	0.497	4.16	<0.0001
Low/medium support	0.309	2.59	0.005

Results

Table 34 presents summary statistics for ratings for the **Primary Task Support** category. Note that the rounded mean column is simply the mean rounded to the nearest integer. The Min and Max columns provide the minimum and maximum ratings, respectively, and for any item that has a range of 1 between the minimum and maximum, the rounded mean can be interpreted as the "majority vote" rating. Among the items, all agree that the system provides strong support for Self-Monitoring, and the majority agree that it provides strong support for Tailoring and Personalization. All agree that the device provides low/intermediate support for Tunnelling, and the majority find low/intermediate support for Reduction and Simulation as well. The majority found that the device provides no support for Rehearsal. The relatively poor implementation of Simulation and Rehearsal is disappointing in terms of behavioural support for exercise persistence as both may encourage goal management, self-regulation and perceived competence; (Bar, 2011; Oettingen, 2012).

Table 34 *Ratings for Primary Task Support Design Category*

Variable	Rounded mean	Mean	Std. dev.	Min	Max
Reduction	0	0.200	0.447	0	1
Tunneling	0	0.000	0.000	0	0
Tailoring	1	0.800	0.447	0	1
Personalization	1	0.600	0.548	0	1
Self-monitoring	1	1.000	0.000	1	1
Simulation	0	-0.400	0.548	-1	0
Rehearsal	-1	-0.800	0.447	-1	0

Table 35 provides summary statistics for the **Dialog Support** category. Liking is the only item judged to provide strong support and all raters agree that the system delivers highly on this item. Observe that for the items Social Role and Praise, the range of ratings is from -1 to 1, creating a rounded mean of zero, which is not especially reliable. Reminders, Suggestion and Similarity also have rounded means of zero, indicating low to moderate support of these items. The majority of panellists agree that the system provides no support for Rewards. The low scoring around Reminders and Suggestions variables is disappointing as these tools are often represented in web and mobile-based support apps targeting exercise adherence and may be effective, (Brannon, Feist, & Updegraff, 2013).

Table 35 *Ratings for the Dialog Support Design Category*

Variable	Rounded mean	Mean	Std. dev.	Min	Max
Praise	0	0.000	0.707	-1	1
Rewards	-1	-0.800	0.447	-1	0
Reminders	0	-0.200	0.447	-1	0
Suggestion	0	-0.400	0.548	-1	0
Similarity	0	0.400	0.548	0	1
Liking	1	1.000	0.000	1	1
Social role	0	-0.400	0.894	-1	1

Table 36 summarizes ratings for the **Credibility** category. Surface Credibility and Real World Feel are given the highest ratings by the majority of panellists but the majority gives Authority, Third Party Endorsements and Verifiability low/moderate support ratings. For Trustworthiness and Expertise, ratings range from -1 to 1 and therefore have a mean of low/moderate support but are unreliably rated as such.

Table 36 *Ratings for the Systems Credibility Design Categor*

Variable	Rounded mean	Mean	Std.dev.	Min	Max
Trustworthiness	0	0.000	0.707	-1	1
Expertise	0	-0.400	0.894	-1	1
Surface credibility	1	0.800	0.447	0	1
Real world feel	1	0.800	0.447	0	1
Authority	0	-0.400	0.548	-1	0
Third-party endorsements	0	-0.200	0.447	-1	0
Verifiability	0	-0.200	0.447	-1	0

Table 37 provides ratings for the Social Support category. All panellists agree that the system provides high support for Social Facilitation while the majority of panellists rate Social Learning and Social Comparison as having high support. All panellists agree on low/intermediate support for Cooperation, and the majority says the same for Competition and Recognition. Normative Influence is also rated at low/intermediate by the rounded mean, but has a range of low to high support.

Table 37. *Ratings for the Social Support Design Category*

Variable	Rounded mean	Mean	Std. dev.	Min	Max
Social learning	1	0.600	0.548	0	1
Social comparison	1	0.600	0.548	0	1
Normative influence	0	0.000	0.707	-1	1
Social facilitation	1	1.000	0.000	1	1
Cooperation	0	0.000	0.000	0	0
Competition	0	0.400	0.548	0	1
Recognition	0	0.400	0.548	0	1

Table 38 summarises the ratings by design category and provides *p* values for the two-sided test of the null hypothesis that the mean is different than 0. Note that each of the *p* values is based on a *t* statistic with 34 degrees of freedom since each domain has 7 items and 5 raters. Dialog Support is the lowest rated category, with a mean of -0.286 that is not significantly different than 0. Both Dialog Support and Systems Credibility categories have means that are not significantly different than zero, or low/moderate in support overall. By contrast, Social Support is statistically significantly above a mean of zero at <0.001 level of significance and Primary Task support is above the mean of zero at a 0.10 level of significance.

Table 38 *Average Rating by Design Category with test of null hypothesis that mean = 0*

Domain	Number of ratings	Mean	Std. dev.	p value	Min of sum	Max of sum
Primary task support	35	1.000	3.266	0.079	-4	5
Dialog support	35	-0.286	2.984	0.575	-4	5
Credibility support	35	0.286	2.628	0.524	-2	4
Social support	35	2.143	1.773	0.000	0	5

Summary of Findings

RQ16

How completely and effectively does the *movescount.com* system implement the recommended BCSS-PSD design techniques?

The system, according to the expert panel falls short of implementing the idealized levels of the BCSS-PSD design principles, by category as seen in Table 39.

Its Primary Task Support functions are strongest in what would be expected of a system that allows an individual to capture and monitor their exercise efforts, targets and plans; it is easily tailored to suit, highly personalised and thorough in its self-monitoring capabilities.

The overall moderate operationalization of adequate Dialog Support is of concern given its salience in encouraging continued use of the system as established in Chapter 5. In particular, overlooking the use of praise and reward in the implementation of dialogue should be an area of concern to the vendor. Credibility Support reads as something of a mixed bag which is unsurprising as movescount.com is a commercial operation and may be subject to a degree of compromise and lack of impartiality; it is not distributed and supported by a government entity or independent professional body.

Table 39 *Overall Panel Expert Ratings for BCSS-PSD Design Techniques Implemented in movescount*

Design technique	Overall Panel rating for level of support
Primary Task Support	
Reduction	Moderate
Tunneling	Moderate
Tailoring	Strong
Personalization	Strong
Self-monitoring	Strong
Simulation	Moderate
Rehearsal	None
Dialog Support	
Praise	Moderate
Rewards	None
Reminders	Moderate
Suggestion	Moderate
Similarity	Moderate
Liking	Strong
Social role	Moderate
Credibility	
Trustworthiness	Moderate
Expertise	Moderate
Surface credibility	Strong
Real world feel	Strong
Authority	Moderate
Third-party endorsements	Moderate
Verifiability	Moderate
Social Support	
Social learning	Strong
Social comparison	Strong
Normative influence	Moderate
Social facilitation	Strong
Cooperation	Moderate

Design technique	Overall Panel rating for level of support
Competition	Moderate
Recognition	Moderate

Given the inclusion by movescount.com of an extensive online, closed social network and the option to publish to external social media accounts, it's unsurprising the system is rated strongly for most of the Social Support techniques. The lesser rating of recognition seems consistent with its lack of praise and reward features. The lack of head to head competition functions is curious given its popularity in competitor sites such as *fitbit*®.

Discussion

The salience of the findings from Study Three is constrained by the small number of panellists that could be convened to complete the assessment. That said, signs do emerge from the experts that the system under examination only partially implemented the ideal level of BCSS PSD features. The relatively weak implementation of Simulation and Rehearsal are puzzling as both are imagery-intensive techniques that may be important in planning and executing physical activity techniques, (Holmes & Calmels, 2008). The omission of adequate levels of praise and reward for users interacting with the system to better understand and support their exercise efforts contrasts with their use in mobile apps and so-called *serious games*, (Baranowski, Thompson, Buday, Lu, & Baranowski, 2010; Thompson et al., 2010). Although, the evidence to verify the efficacy of behaviour change features in apps and wearable systems is still lacking, (Case, Burwick, Volpp, & Patel, 2015a). The weak rating for Verifiability may be a reflection of the lack of independent assessment of the accuracy of the Suunto measurement sensors. Researchers are only just meeting concerns over the accuracy of digital exercise tracking devices, (Aziz & Robinovitch, 2011) and (Editor, 2013). Given the push by wearables vendors into the true healthcare space, surely the accuracy and fidelity of the data they generate must come under greater scrutiny by researchers and regulatory authorities. The unsatisfactory rating of Third Party endorsements may be an oversight on behalf of most of the panel as movescount.com has an extensive and well-patronized (as measured by downloads metred online) library of third party apps. The omission of recognition and competition features in the movescount.com online social network contrasts to recommendations that encourage vendors to include motivational triggers in the form of recognition and awards as they are so strongly correlated to completion of physical activity goals in an online environment, (Ba & Wang, 2013.).

The work completed in this chapter and chapter 4 does beggar the question as to when and how behaviouralists could engage with product development teams to make best use of health behaviour change and persuasive systems practices. It also creates implications for persuasuive design of similar apps. These implications are treated in detail in Appendix L of the thesis.

Chapter 7

Introduction

The output from Study One and Study Two identified the exceptional exercise and online social activity behaviour of those users of the system that choose to publish their moves to Twitter. This phenomenon led to an investigation of the nature of a random sample of tweets from a subset of the total user population of *movescount.com*, their exercise session content, user demographics, physical activity type and an examination of the online social influence rating of these users as determined by their KLOUT score. Unfortunately, the vendor refused to release tweeting data for any of the users from Study One or Study Two. This led to generation of an extraneous data set from a group of unrelated users that irrespective still use the movescount.com system and tweet their exercise sessions to the Twitter platform.

A number of analytic processes were employed to satisfy the thesis goal and the esearch questions for this study.

Goal Six

To determine the association between an individual's published *movescount.com* exercise moves to Twitter and their online social influence as calculated by the KLOUT service

Research Questions

RQ17 What demographic variables characterize the sample of Twitter users?

RQ18 Do those individuals who publish their moves to Twitter and revealing a higher online social influence (KLOUT) score demonstrate higher exercise effort measures by way of distance, speed, and training effect (TE)?

RQ19 Is there any association between those users who publish their exercise sessions using additional devices and services and their KLOUT score?

RQ20 Is there any association between those users who publish their exercise sessions using additional devices and services and their exercise effort measures?

Method

Active users of the Suunto system who publish their exercise moves as tweets to the Twitter social media service were identified using a common Twitter search #hashtag string known to be unique to this user community and their tweets archived using Hootsuite software. These public tweets were collected over a 28-day period and disassembled to identify and record exercise and online social influence scoring data. All user account identifying variables and corresponding data values for each and every Twitter user in this sample were removed to ensure privacy and anonymity. This data was then examined using Stata 13 using descriptive and regression analysis techniques. A quantitative methods approach is used in this examination of the published, public exercise sessions (moves) of a random sample of *movescount.com* users. Along with descriptive statistical summaries of the sample data, multivariate regression techniques are applied to the data to determine the presence of associations that may exist between exercise-Tweeter demographic characteristics, activity type, exercise effort-outcome variables and online social influence rank based on *klout.com*[10] scoring. The specific research questions to be answered through this data analysis are:

[10] Klout is a website and mobile app that uses social media analytics to rank its users according to online social influence via the "Klout Score", which is a numerical value between 1 and 100. In determining the user

Results

RQ17

What demographic variables characterize the sample of Twitter users?

Descriptive statistics for Movescount moves tweeted

There are 656 unique Twitter handles in this sample, with 562 males (85.67%), 37 females (5.64%) and 57 (8.69%) of those whose gender could not be identified. These users published a total of 2,079 exercise sessions (moves) from their Suunto exercise devices published as tweets over the recording period. Except where it is noted otherwise, for each of the statistics presented below, the averages are computed based on each user and then these averages are again averaged to obtain averages per user. First averaging across users and then using those statistics for further analysis makes for an inference made across a population of people because each person counts the same. To understand this, if by contrast, we took simple averages using all 2,079 observations, the inference would be with respect to exercise sessions, that users with multiple exercise sessions would inherently be counted more than users with only one exercise session.

Table 40 provides descriptive statistics for general tweets, duration of moves, distance in km, average speed in km/h, KLOUT, number of followers and number of people followed averaged across individuals' averages. For the sample, the average person tweeted 2,442 times – these are general tweets of all types not the number of moves published as tweets and refers to all tweets published since the individual

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score, Klout measures the size of a user's social media network and correlates the content created to measure how other users interact with that content ("Klout," 2014).

became a Twitter account user not just the period for which records were kept for this study; no greater fidelity was possible due to constraints of the archiving tool. The data capture and archive process did not include date of commencement of Twitter account usage. Although on average, women tweeted about 150% as often as men (3,592 versus 2,358) given the enormous variability in the number of tweets this difference is not statistically significant. The variability in tweets across people is also well-represented in the range, where the minimum average number of times a person tweeted their sessions was 6 versus a maximum average number of times a person tweeted of 86,200 which is a figure difficult to explain in terms of real-world use of the system. This was not a coding error. On average, people follow more people than they are followed by, which is also true of males but not females. For duration, the middle 50 percent of the distribution works out from roughly 45 minutes to 90 minutes for both men and women, although the extremes are as short as 3 minutes on average and as long as 1,391 minutes (about 23.2 hours) which upon examination of such instances was found to be an ultra-endurance activity. The average KLOUT score in the sample is 27, standard deviation of 13, with a high of 68 and a low of 10. The distribution of KLOUT scores for the women in the sample is a rightward shifted version of the distribution for men, as the mean and all of the percentiles are higher for women than for men, although the means are not statistically significantly different.

Table 40 *Descriptive statistics for tweets, duration and KLOUT score*

Variable	N	Mean	Std. dev.	Min	Max	p25	p50	p75
Full sample								
General tweets	656	2,442.351	5,832.613	6	86,200	235	658	2,162
Duration	651	83.213	83.813	3	1,391	44	62	95
Distance, km	601	15.772	17.530	0	161.07	6.197	10	19
Avg. speed, km/h	600	11.075	5.709	0	39.104	7.891	10	13
KLOUT score	552	27.084	13.507	10	68	16	23	35
N followers	656	334.994	1,199.249	0	23,300	34	96	218
N following	656	371.828	988.698	0	23,000	81	176	411
Males								
General tweets	562	2,358.379	5,638.743	8	86,200	235	664	2,099
Duration	558	83.591	86.918	3	1,391	43	64	95
Distance, km	517	15.974	17.794	0	161	7	11	20
Avg. speed, km/h	516	11.284	5.716	0	39	8	11	13
KLOUT score	475	26.940	13.402	12	68	16	23	34
N followers	562	319.710	1,205.525	0	23,300	33	96	218
N following	562	378.048	1,053.916	0	23,000	82	179	416
Females								
General tweets	37	3,592.548	8,403.540	6	49,250	274	805	3,453
Duration	37	80.466	53.858	9	246	49	60	102
Distance, km	34	13.635	13.045	0	57	5	9	22
Avg. speed, km/h	34	9.622	4.833	0	21	8	10	12
KLOUT score	33	33.821	15.889	13	66	18	35	43
N followers	37	747.731	1,760.966	9	7,603	59	135	353
N following	37	446.127	522.032	7	2,023	103	236	522
Gender undefined								
General tweets	57	2,524.652	5,747.441	13	35,700	259	566	2,239
Duration	56	81.265	67.819	9	433	46	64	90
Distance, km	50	15.137	17.614	0	83	5	9	18
Avg. speed, km/h	50	9.908	6.000	0	27	6	10	13
KLOUT score	44	23.583	11.056	10	51	16	19	31
N followers	57	217.766	374.901	4	1,701	34	85	191
N following	57	262.265	328.901	7	1,843	51	128	320

Table 40 also shows the average distance and speed for each person's exercise session, which is 15 km and 11 km per hour respectively for the full sample. Clearly speed and distance vary across activity given the nature of each by way of environment, equipment and biomechanical specifics. The average speed in Table 40 is about the same as the averages for Roller Skating, Rowing, Running, Track and Field, Trail Running and Treadmill, Circuit Training, Climbing, Cross Fitness, Golf, Martial Arts, Mountaineering, Multisport, Orienteering, Rugby, Soccer, Swimming Tennis, Trekking, Walking and Weight Training are all substantially below average. Cycling, Motorsports, Mountain Biking, Roller Skating and Triathlon are all substantially above average speed. Substantially *above average KLOUT scores occur in Canoeing, Climbing, Kayaking, and Motor Sports*, although as is determined subsequently, primarily Number of Followers and Number of Tweets explain KLOUT scores.

A frequency count for Move Intensity by Gender is depicted in Figure 45. Note that between 30 and 40 percent of move intensities were not recorded for each of these groups. Upon investigation, it was revealed that the user at the movescount.com system-end might treat this measure as an option only when they elect to publish a move to Twitter. Women have slightly fewer low and moderate intensity moves than men, and a higher proportion of moves that are at least as intense as hard (77 percent versus 67 percent), although women have no maximal intensity moves in this sample.

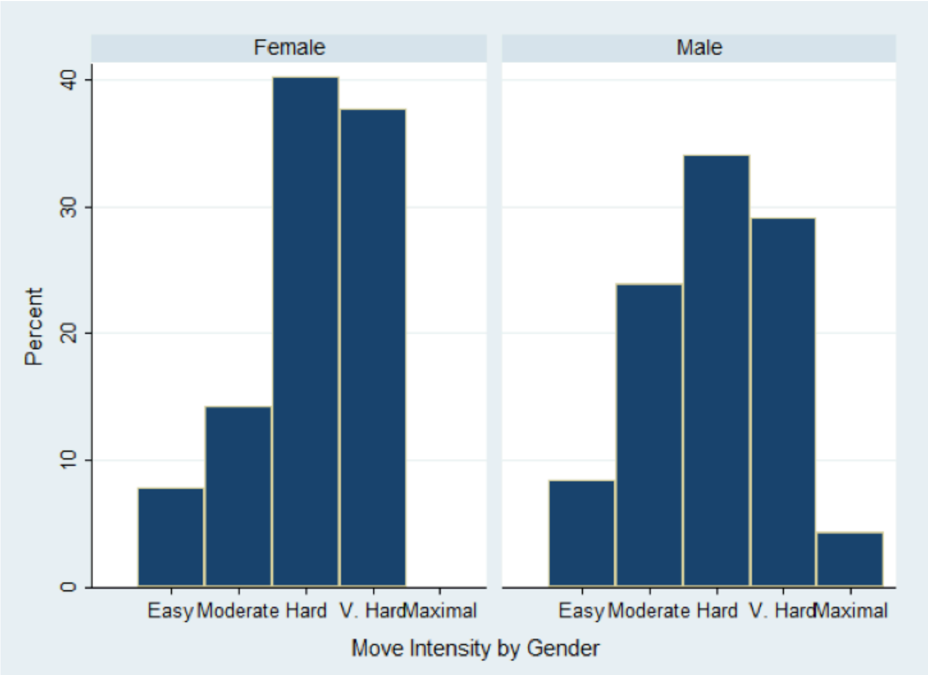

Figure 45. Frequency histogram - move intensity by gender

As with speed and distance, Move Intensity is closely related to activity. Half or more of the moves for which intensity was recorded are High or greater than High were for Badminton, Canoeing, Circuit training, Climbing, Cross training, Cycling, Indoor Cycling, Indoor Rowing, Martial Arts, Multisport, Orienteering, Roller Skating, Rowing, Running, Soccer, Squash, Swimming, Tennis, Track and Field, Trail Running, Treadmill, Trekking, Triathlon. In contrast, the majority of recorded moves are less than Hard for Aerobics, Cross Fit, Dancing, Golf, Ice Skating, Kayaking, Mountain Biking, Roller Skiing, Roller Skating, Rugby, Stretching, Walking, Weight Training, Windsurfing and Yoga.

RQ18

Do those individuals who publish their moves to Twitter with a higher online social influence (KLOUT) score have higher exercise effort measures by way of distance, speed, and training effect (TE)?

Regression analyses for Movescount moves tweeted

The relationship between the variables of distance, gender, KLOUT score and activity is investigated by a regression of distance on these variables, the coefficients of which are presented in Table 41. Because individuals may pursue different activities in different moves, the move is the unit of observation, and there are 1,096 moves for which distance data is available and for which there are at least five instances of the activity in the source data file. The overall *F* statistic for the regression has a value of 1,028.82 and 13 and 1,082 degrees of freedom, implying a *p* value of less than 0.0001, which means that the regression model provides a significantly better estimate of the mean distance than the sample mean distance. The *R squared* for the regression is 0.32, implying 32 percent of the variation in distance in the sample is explained by the regression model. To avoid perfect multi-collinearity, one of the indicator variables for activity and gender has to be omitted (i.e., included in the estimated constant for the regression) and in this instance, the omitted activity is Cycling and the omitted gender is Female. This means the estimates for each activity are estimates of the amount by which the average distance associated with that activity differs from the average distance covered while Cycling and the estimate for Male is an estimate of the difference between the average distance covered by a Female and the average distance covered by a Male, controlling for activity and KLOUT score. Only Mountain Biking and Triathlon cover statistically insignificant different distances than cycling, and the remaining activities cover significantly less distance than Cycling. *Neither KLOUT scores nor gender are significantly associated with distance once activity is controlled for*. This is to say that an individual's estimated online social influence has nothing to do with how far they cover in an exercise session that they choose to publish to Twitter.

Table 41 *Regression of Distance on Gender, KLOUT score and Activity*

	Coefficient	Std. Err.	t	P>|t|	95% LCL	95% UCL
Constant	31.278	2.937	10.650	0.000	25.516	37.041
Male	0.288	2.361	0.122	0.903	-4.345	4.922
KLOUT score	0.033	0.026	1.264	0.207	-0.018	0.085
<u>Activity</u>						
Mountain biking	-2.689	3.375	-0.797	0.426	-9.312	3.934
Multisport	-20.908	5.986	-3.493	0.000	-32.654	-9.162
Roller skating	-11.204	1.646	-6.805	0.000	-14.435	-7.974
Running	-22.375	1.678	-13.334	0.000	-25.668	-19.083
Swimming	-30.180	1.691	-17.852	0.000	-33.497	-26.863
Tennis	-31.168	1.789	-17.420	0.000	-34.678	-27.657
Trail running	-17.788	1.850	-9.617	0.000	-21.418	-14.159
Trekking	-22.314	2.286	-9.762	0.000	-26.800	-17.829
Triathlon	8.858	10.079	0.879	0.380	-10.920	28.635
Walking	-22.513	3.894	-5.781	0.000	-30.154	-14.871
Weight training	-32.450	1.653	-19.635	0.000	25.516	37.041

RQ19

Is there any association between those users who publish their exercise sessions using additional devices and services and their KLOUT score?

RQ20

Is there any association between those users who publish their exercise sessions using additional devices and services and their exercise effort measures?

Probit regression

To explore the nature of the intensity of exercise activity and the connectedness, if any, with the online social influence of the exerciser measured by the KLOUT score, an ordered *probit regression* is used. This method of regression analysis, also called a *probit model*, is typically used to model dichotomous or binary outcome variables. In the probit model, a linear combination of the predictors is mapped onto the probability of observing a success via a link function, which, for probit models, is the inverse standard normal pdf. Because there are five different categories, there are four "cut point" values, namely, the cut points between Easy and Moderate, Moderate and Hard, Hard and Very Hard, and Very Hard and Maximal, and the ordered probit regression provides estimates associated with these cut points. Second, for any independent variables in the model, their estimated coefficient in the ordered probit regression model indicates the change in the underlying (and unobserved) propensity to choose a higher category on the Likert scale.

Table 42 presents estimated coefficients for the ordered probit regression of Move Intensity on Gender, KLOUT score, whether the exerciser has Another Device or Online Exercise Service and their activity. It is possible for Twitter users to publish an exercise session either using multiple devices similar to the Suunto AMBIT and or to share an exercise session through a number of online services such as Endomondo and I Map My Run amongst others. This multiple ownership and publishing variation has been identified as an area of interest. To be included in the sample, a user was required to have at least five observations of the activity, but because some activities have missing values for intensity, the sample size falls to 810. For the sample of 810, we are able to reject the null hypothesis that all coefficients in the model are equal to zero at a significance level less than 0.001. Note that to obtain a coefficient on KLOUT score that is conveniently scaled, the KLOUT score is divided by 100. That is, intensities are on a scale of 1 to 5, and KLOUT scores are an order of magnitude larger than that, so that their regression coefficients would be too small to display and discern if we did not divide KLOUT score by 100. Because this model does not contain an estimated constant, all of the activities are included.

Table 42 *Ordered Probit Regression of Move Intensity on Gender, KLOUT Score and Activity*

	Coefficient	Std. Err.	z	P>|z|	95% LCL	95% UCL
Cut 1	-1.781	0.439			-2.641	-0.921
Cut 2	-0.726	0.434			-1.577	0.124
Cut 3	0.309	0.434			-0.541	1.159
Cut 4	1.778	0.441			0.913	2.643
Male	-0.492	0.157	-3.130	0.002	-0.801	-0.184
Has other device	-0.208	0.144	-1.450	0.147	-0.490	0.073
Klout score/100	-0.060	0.279	-0.214	0.831	-0.606	0.487
Activity						
Cross fit	-0.739	0.478	-1.545	0.122	-1.677	0.198
Cross trainer	-0.124	0.472	-0.263	0.793	-1.048	0.800
Cycling	-0.090	0.406	-0.222	0.824	-0.885	0.705
Indoor cycling	0.386	0.443	0.872	0.383	-0.482	1.255
Indoor rowing	-0.222	0.839	-0.265	0.791	-1.866	1.422
Kayaking	-1.807	0.825	-2.192	0.028	-3.423	-0.191
Martial arts	0.292	1.119	0.261	0.794	-1.901	2.485
Mountain biking	-0.404	0.437	-0.923	0.356	-1.261	0.453
Multisport	0.233	0.511	0.456	0.649	-0.768	1.234
Roller skating	0.302	0.722	0.418	0.676	-1.114	1.717
Running	0.646	0.400	1.615	0.106	-0.138	1.430
Soccer	1.107	0.737	1.501	0.133	-0.339	2.552
Swimming	1.547	0.748	2.068	0.039	0.081	3.013
Tennis	-0.440	0.624	-0.704	0.481	-1.663	0.784
Trail running	0.434	0.413	1.051	0.293	-0.375	1.243
Treadmill	1.106	0.627	1.763	0.078	-0.123	2.335
Trekking	-0.159	0.501	-0.317	0.751	-1.142	0.824
Triathlon	0.872	0.566	1.540	0.124	-0.238	1.982
Walking	-1.774	0.586	-3.027	0.002	-2.923	-0.626
Weight training	-0.713	0.426	-1.675	0.094	-1.548	0.121
Tennis	-0.440	0.624	-0.704	0.481	-1.663	0.784
Trail running	0.434	0.413	1.051	0.293	-0.375	1.243

The estimated cut points in Table 42 indicate the *rarity of exercise sessions that are either very hard or maximal in the sample*. From the other estimated coefficients, *KLOUT score and whether the person publishes tweets using Another*

*Additional Device do not significantly affect the probability of having a workout of various intensities***.** The model does not have much explanatory power, but what value it does have may be in the coefficients for Males, which is significantly lower for Females and *implies on average less intense workouts for Males than Females*, and in the activities that have coefficients that are significantly different than zero. The only activity with a significantly positive coefficient at the 0.05 level of significance is Swimming. Kayaking and Walking are significantly negative at the 0.05 level of significance. *The analysis fails to hold true any assertion that those who have higher online social influence as measured by KLOUT Scores somehow workout more intensely*.

Continuing with this theme, an exploration was conducted of the relationships between Total Tweets, KLOUT score and Activity. Total Tweets was regressed on KLOUT score and an indicator for each activity for which there were five or more observations of the activity in the sample. Results are provided in Table 43 for the resultant 1,271 observations. The regression F statistic is 332.93, and has 23 and 1,247 degrees of freedom, and therefore a p value less than 0.001, implying that the regression does a better job of predicting Total Tweets than the sample average of Total Tweets. The R squared for the regression is 0.28, implying 28% of the variation in dependent variable, Total Tweets, is explained by the independent variables. To avoid perfect collinearity, one activity is omitted and included in the constant, Circuit Training is the omitted activity, and estimates for the remaining activities are expressed as differences from the constant, or in other words as differences from the mean for Circuit Training, holding all other variables constant. The only activities that have significantly different means than Circuit Training are Indoor Rowing and Roller Skating, with significantly larger numbers of Tweets, and Scuba Diving, with significantly fewer Tweets. The variance inflation factors were based on each activity, and three activities had variance inflation factors greater than 10, which is a commonly recommended signal of collinearity. The square root of the variance inflation factor indicates how many times higher the estimated standard error is than it would be if the variable were orthogonal to all other variables in the model and permits a check of whether the results would change if a variable were orthogonal to all other variables. Running is the only activity for which collinearity may be affecting results in a manner that would lead to different inference. The average number of tweets by runners is 2,602 and by cross trainers, 878, a difference that is statistically significant using an unequal variances *t* test ($SE = 293.965$, $p < 0.001$). KLOUT score is significantly associated with Total tweets, with each additional point of KLOUT score implying nearly that the average number of tweets is about 200 tweets larger. There is some evidence that having Another Device is associated with more tweets, with the point estimate of an additional 1,271 tweets if a person has another device significant at the $\alpha = 0.10$ level of significance. *Once the effect of KLOUT score is controlled for, there is no statistically significant difference between the number of Tweets made by Males and Females.*

Table 43 *Regression of Total Tweets at each Move on KLOUT score*

Activity	Coefficient	Std. Err.	t	P>|t|	95% LCL	95% UCL
Constant	-3,264.662	1,252.331	-2.607	0.009	-5,721.572	-807.753
Has other device	1,271.186	772.953	1.645	0.100	-245.247	2,787.618
Male	-294.553	991.197	-0.297	0.766	-2,239.152	1,650.047
KLOUT score	198.779	15.790	12.589	0.000	167.802	229.756
Cross fit	1,389.096	1,229.250	1.130	0.259	-1,022.532	3,800.725
Cross trainer	826.501	642.067	1.287	0.198	-433.150	2,086.152
Cycling	792.134	697.216	1.136	0.256	-575.713	2,159.980
Indoor cycling	1,048.033	770.421	1.360	0.174	-463.433	2,559.500
Indoor rowing	1,720.078	651.246	2.641	0.008	442.417	2,997.738
Kayaking	-760.449	2,187.979	-0.348	0.728	-5,052.978	3,532.081
Martial arts	353.250	1,159.435	0.305	0.761	-1,921.409	2,627.910
Mountain biking	-297.051	731.605	-0.406	0.685	-1,732.365	1,138.263
Multisport	-520.960	854.900	-0.609	0.542	-2,198.163	1,156.244
Roller skating	5,916.333	636.531	9.295	0.000	4,667.543	7,165.123
Running	706.636	659.626	1.071	0.284	-587.465	2,000.737
Scuba diving	-1,364.891	674.008	-2.025	0.043	-2,687.206	-42.576
Soccer	3,198.932	1,847.834	1.731	0.084	-426.278	6,824.141
Swimming	78.153	716.142	0.109	0.913	-1,326.825	1,483.131
Tennis	-2,700.614	1,629.474	-1.657	0.098	-5,897.430	496.202
Trail running	75.201	691.543	0.109	0.913	-1,281.515	1,431.918
Treadmill	3,530.329	2,834.071	1.246	0.213	-2,029.749	9,090.406
Trekking	213.457	1,035.849	0.206	0.837	-1,818.745	2,245.659
Triathlon	860.281	1,703.312	0.505	0.614	-2,481.395	4,201.957
Walking	2,052.612	1,784.196	1.150	0.250	-1,447.748	5,552.971
Weight training	603.079	779.221	0.774	0.439	-925.650	2,131.809

Taking this line of investigation to its end run with the sample data provides an exploration of variables associated with the KLOUT score. To do this, each individual's average KLOUT score is regressed on Gender, an indicator for the user having Another Device, the user's average Number of Followers, the average Number of People the User is Following, the number of Tweets and the Move indicators of average speed, average duration and average distance. Due to differences in scale, KLOUT scores potentially range from 0 to 100, and Followers and Tweets are in their many thousands then the Number of Followers, Number of People Following, and Number of Tweets are divided by 1,000 before appearing in the regression model. This regression analysis is depicted in Table 44. There are 471 observations. The R squared for the regression is 0.29, and the *F* statistic is 8.06 with 9 and 461 degrees of freedom, associated with a *p* value of less than 0.0001. There is some evidence that Males have an average KLOUT score that is lower than Females, with the point estimate of average male score being the average female score minus 4.719 (*p* value = 0.059). None of the Move indicators, Speed, Distance, or Duration, has a statistically significant effect on KLOUT score. The two variables that have significant effects on KLOUT score are Number of Followers, with a point estimate of an increase in average KLOUT score of 2.91 for each additional 1,000 Followers, and Number of Tweets, with a point estimate of an increase in KLOUT score of 0.838 for each additional 1,000 Tweets. This is consistent with what evidence exists in the literature which points to both these variables as likely candidates for being incorporated into the KLOUT score algorithm, ((Campo-Ávila, Moreno-Vergara, & Trella-López, 2013; Nguyen & Zheng, 2014).

Table 44 *Regression of Average KLOUT Score on Gender, Social Behaviour Indicators and Move Indicators*

	Coefficient	Std. Err.	t	P>|t|	95% LCL	95% UCL
Constant	28.921	3.150	9.181	0.000	22.731	35.112
Male	-4.719	2.491	-1.895	0.059	-9.614	0.175
Has-other device	3.357	2.765	1.214	0.225	-2.076	8.790
N-followers, 1000s	2.910	0.730	3.986	0.000	1.476	4.345
N- following1000s	0.256	1.635	0.156	0.876	-2.957	3.469
Duration, minutes	0.006	0.014	0.447	0.655	-0.021	0.034
Speed km/h	-0.119	0.167	-0.713	0.476	-0.448	0.209
Distance, km	0.026	0.071	0.362	0.717	-0.113	0.165
Has other device*Tweets/1000	-0.494	0.375	-1.317	0.188	-1.231	0.243
Tweets/1000	0.838	0.270	3.109	0.002	0.308	1.368

Some conclusions may be drawn from this analysis. There is a clear bifurcation between KLOUT scores and Social Behaviour Indicators and Move

Indicators. *KLOUT scores never have any significant effects on any of the Move Indicators, and these indicators in turn, do not have any significant effects on KLOUT scores***.** Instead, Activities tend to be the variables that are best able to explain Move Indicators and the Number of Followers and Tweets are the variables that are significantly associated with KLOUT score.

Finally, there was not found to be many significant differences between the genders. There is some evidence that after controlling for Tweets and Number of Followers, Females have higher KLOUT scores than Males.

Summary of Findings

RQ17 What demographic variables characterize the sample of Twitter users?

85% of the sample population are male. In terms of exercise duration the middle 50 percent of the distribution works out from roughly 45 minutes to 90 minutes for both men and women. The average KLOUT score in the sample is 27, standard deviation of 13, with a high of 68 and a low of 10, above average KLOUT scores occur in Canoeing, Climbing, Kayaking, and Motor Sports. Women have slightly fewer low and moderate intensity moves than men, and a higher proportion of moves that are at least as intense as hard (77 percent versus 67 percent),

RQ 18 Do those individuals who publish their moves to Twitter with a higher online social influence (KLOUT) score have higher exercise effort measures by way of distance, speed, and training effect (TE)?

No they do not. There is no evidence for online social influence as measured by an individual's KLOUT score affecting the intensity of exercise efforts published as movescount moves to Twitter.

RQ19 Is there any association between those users who publish their exercise sessions using additional devices and services and their KLOUT score?

There is some evidence that having Another Additional Device is associated with more tweets.

RQ20 Is there any association between those users who publish their exercise sessions using additional devices and services and their exercise effort measures?

Those individuals who publish tweets using Another Additional Device in addition to their Suunto systems do not significantly show any probability of having a workout of various intensities over and above those who do not publish their exercise tweets using Another Additional Device.

Discussion

Study Four arose from the interesting findings of Study One and Two that showed those movescount.com users who published their exercise sessions to Twitter as well as to the movescount.com system itself tended to use the movescount.com system more frequently and upload a greater number of exercise sessions compared to their peers. It was hypothesised that perhaps these individuals, given their proclivity for Twitter use, also had a high level of online social influence. This identification of individual's with high online social influence has become the focus of marketers and behaviour change researchers (Bevilacqua, Clare, Goyal, & Lakshmanan, 2013) as they seek cost effective means to exert targeted purchase and behavioural change across large numbers of people. Keller & Berry (2003) termed those who are sought after by others for their opinions on products, services, events and others in the offline world as **i***nfluentials*. It was reasoned that knowing these corresponding users in the online world and learning more about them might provide a starting point for connecting with them for means of positively affecting the exercise behaviour of others.

The dataset and techniques used to answer the resultant research questions may not be suitable to reach this end. The requirement for total anonymity precluded any meaningful communication with the users themselves, a base position stemming from the vendor's reluctance to allow the required examination of users from the datasets used in Study One and Two. If future efforts can elicit a vendor-independent dataset, ethical and end user approval then the motivation and personality attributes of the target users are more likely to be identified, classified and understood.

The work completed in Study Four failed to establish any association between an individual user's online social influence score as measured by the KLOUT service and the published attributes of their exercise effort that could be construed in any way as remarkable. This is evidenced in the regressions models revealing Average KLOUT scores on numbers of followers and exercise intensity (R squared = 0.29), total tweets on KLOUT score and activity (R squared = 0.28) and total distance on gender, KLOUT score and activity (R squared =0.32) all having a fairly modest ability to explain variation in their respective dependent variables. A high KLOUT score does not have a relationship with an individual's exercise behaviour. The online social factors of a user's popularity on Twitter as measured by the number of followers they have and how frequently they tweet appear to have no bearing on the nature of their exercise bouts. Determining that individuals that are involved with canoe, kayak and motor sports exhibited substantially higher KLOUT scores on average compared to the rest of the sample population of 656 unique Twitter handles, may point to Twitter offering potential as a communication and recruitment tool for these particular sports.

Chapter 8

Discussion

The investigative process used across the four composite studies of this thesis uncovered not only answers to the research questions initially raised but yielded further observations of interest. Study One analyses produced a picture of the fundamental demographic and anthropometric features of the population of active athletes using the digital exercise tracking system that was examined. It revealed exercise behaviour of interest from those users who frequently publish exercise sessions to Twitter, amongst other associations between online social phenomenon and general system usage. Study Two used a mix of qualitative techniques arising from a psychosocial scale administered to a subset of the user population from study one. These techniques were used to better understand how the design of the software used in the movescount.com system might affect usage of the system and a preference to continue use of the system. The third study canvassed the learned views of experts in the BCSS theory and persuasive systems design about the design of the movescount.com system itself. Finally, Study Four, inspired by the social activity measures and exercise associations from Study One delved into the potential role of online social influence on the exercise behaviour of a discreet subset of the movescount.com user population that tweeted their exercise sessions.

The first study provided an insight into the demographic and anthropometric characteristics of the Suunto movescount.com population sample of 20,000 users. This group was found to be predominantly male (89.36%) who indulge in running as their preferred physical activity (28.3%). The second study comprising a subset from this group of 521 respondents was similarly skewed toward males (92%) and indicated a high level of education with 53% having some experience of graduate school. An extensive search of the literature indicates this is the first time such a figure for gender proportions in a large digital exercise tracking population sample has been produced. Clearly, there is room to grow the number of female users of this system. In terms of external social media account ownership, users have a strong preference for Facebook (11.02%), with Twitter also popular (2.64%) but overall the proportion of all users having any such account is modest (16.90%). It would appear that Suunto movescount.com users are content to use the device almost exclusively for its primary purpose, recording and managing exercise data online and restricting their social network interactions to the in-house functions of the system. There is not a strong inclination from the majority of users to share their exercise information with others through external social media channels. In terms of age, members of the sample population are on average 39.03 years of age (*SD* = 9.97) and logged into the system on average 7.37(*SD* = 18.04) times with 95.9% having fewer than 40 logins and males logging in an additional 2.45 times compared to females.

Anthropometrically, the user population seemed to fit a reasonably lean profile with a Body Mass Index (BMI) score (mean = 24.88) which is unsurprising given the finding from the survey sample population used in study two that shows 85.41% of that population subset were exercising regularly in the 12 months prior to purchasing a Suunto system. The users in study one worked out an average of one to three hours per week based on an average Fitness Index (FI) of 5.7 as defined by the movescount.com system. The systems users could be profiled as predominantly lean and active. It was also discovered that those with leaner BMI scores logged into the system more often. A possible reason for this may be that leaner, fitter users are training more regularly and individuals that exercise more frequently tend to have lower BMI scores (Garcia, 2012). However, there is insufficient evidence to speculate further.

Social involvement online in the movescount system encompasses a number of functions, the first of which is the following activity whereby one user can follow one or more others, an activity that may or not be reciprocated. The mean number of people a user follows is 3.11 with $SD = 9.362$ for a sample size of 2,411. The number of people a user is followed by has a mean of 1.71 and a $SD = 7.4$ for a sample of 4,745 people. Regression analysis for Login Count on following behaviours indicates that the Login Count for a user increases by an average of 11.436 ($SE = 0.949$, $p < 0.001$) for each additional follower. The regression model for the mean Number of Moves (exercise sessions uploaded by a user to the movescount.com system) as a linear function of the Number of People a User Follows reveals a slope of 0.220 ($SE = 0.046$, $p < 0.001$), implying the average number of moves for a user increases by 0.22 for each additional person a user follows. The implication from analysis of the following behaviour on the system is that both the average number of logins and the average number of moves increase with the number of people a user follows or is followed by. As to why this may be the case, it is difficult to be absolutely certain. On the face of it, there exists a synergy between system usage and passive social relationships expressed as following behaviour such that the more interest that is shown by an individual toward another, the more likely it is they will log in to the system and upload exercise data.

Although there is no existing evidence that examines the dynamics of the following behaviour within the narrow bounds of the Suunto movescount.com or similar populations, (Hutto, Yardi, & Gilbert, 2013) have investigated follower count on Twitter. Their work focused on identifying factors that encouraged an individual's growth in their number of followers and hence their reach of social ties and influence. Because the movescount.com following function does not provide Twitter content equivalence namely through the use of hashtags and tweet-embedded URL links to external content, then the only finding from this particular Twitter study that may have direct relevance is that social behavioural choices can affect an individual's network growth. Both (Hutto et al., 2013) with Twitter analysis and (Donath, 2007) found that choosing to complete user profile elements helps persuade other users of one's authenticity and trustworthiness, making them more likely to become followers. Long, Chen, Wang, Hui, & Vasilakos (2013) in a survey of research into user behaviour in online social networks identified behaviour such as one user viewing another user's profile as a *latent interaction,* by that definition, *following* on movescount.com would constitute a latent interaction between users. A limitation of the current study is the inability to access the necessary data from the Suunto system that reveals the level of completion of an individual user's profile. Having this available would allow examination of the role it may have on influencing follower numbers as a latent interaction and be a worthwhile avenue for future investigation of how profile completion on a digital exercise tracking systems like movescount.com affects an individual's online network growth.

The movescount system also provides for more active online sociability functions for users, in particular *thumbs* and *shouts.* Thumbs are an equivalent of the *like* function found in social networks such as Facebook that allow a user to indicate their approval for another user's uploaded content usually by way of Facebook status updates. Long et al., (2013) based on original investigations by (Wilson, Boe, Sala, Puttaswamy, & Zhao, 2009), define online behaviour such as posting comments on Facebook walls as *interaction graphs*. The *thumb* and *shout* behaviour exhibited by movescount.com systems users may be reasonable corollaries of this behavioural classification. The majority of the thumbs sent, (67.4%) were "self-appreciation," or thumbs that a user sent to their own record. More than 75 percent of users received two thumbs or fewer and only receive thumbs from themselves. The data for thumbs sent reflect the same phenomenon, as more than 75 percent of users send 2 or fewer thumbs and only send thumbs to themselves. This self-appreciation may be interpreted as a form of self-affirmation for exercise by the individual who seems to be signalling to themselves that they are pleased to have exercised and or are pleased with the nature and or outcome of the exercise, the effort involved or the performance reached. Self-affirmation theory maintains that an individual may react to a threat to their self-esteem by using other self-resources to sustain an image of themselves as capable, which primarily involves drawing upon an alternate individual attribute that has proven their self worth in a separate circumstance, (Cohen & Sherman, 2014). The tendency for this sample of Suunto movescount users to send themselves thumbs may imply that these particular individuals draw succour from their exercise competence, a necessary element in experiencing self-efficacy which is seen as vital to an individual's motivation to commence and continue exercise, (Bandura, 2004; Litt, Kleppinger, & Judge, 2002;Martin & Woods, 2012).

The role self-affirmation plays in encouraging physical activity is not extensively researched, although (Cooke, Trebaczyk, Harris, & Wright, 2014) have recently used a controlled trial to investigate the association between self-affirmation and physical activity behaviour. They found self-affirmation, before the provision of information about physical activity and its effects on health, increased self-reported physical activity. Self-affirmed participants reported involving themselves in more physical activity at 1-week follow-up compared with their non-affirmed counterparts.

Self-affirmed participants also demonstrated stronger intentions and more positive attitudes, compared with participants who did not affirm. This particular study suffers from being limited by being totally reliant upon participant self-reported measurement and a lack of long-term post intervention assessment; one week seems insufficient. From the studies comprising this thesis we have identified a strong tendency for a portion of users to self-affirm using the movescount.com *thumbs* function across a free-living population sample base of 20,000 covering a period of over 12 months. This may warrant further investigation, particularly when considered against the evidence that Facebook profiles are self-affirming through satisfying users' need for self-worth and self-integrity; (Toma & Hancock, 2013). This study also revealed a tendency for Facebook users to gravitate toward their online profiles after receiving a blow to the ego, in an effort to remediate their self-esteem. It may be that the users in our study gravitate toward the ego-protective action of positively affirming the completion of an exercise session online. Again, this determination of the self-affirmation value of the profile element of the system could be investigated further.

From the perspective of a digital exercise tracking system like movescount.com, the question could be asked whether the profile function should provide a more immediate summation of the user's exercise progress and achievements through the user interface as a feedback device to assist self-affirmation and self-regulation and thereby encourage greater self-efficacy for exercise. It may also, assuming the same profile is completed with all necessary data, elicit a greater following behaviour from others, according to the literature. Certainly, the evidence from the application of the social cognitive health behaviour model to physical activity is overwhelmingly in favour of the use of self-regulation and feedback to encourage the initiation and continuance of physical activity, (Anderson, Wojcik, Winett, & Williams, 2006;Anderson, Winett, & Wojcik, 2011b; Rovniak et al., 2002; Rimal, 2001) determined that self-efficacy can predict exercise behaviour and further, self-efficacy is not only a determinant of exercise behaviour, but exercise itself is also a source of self-efficacy, (McAuley, Courneya, & Lettunich, 1991).

The movescount.com system is not alone in falling short of providing a complete implementation of ideal levels of health behaviour functionality; (Vandelanotte et al., 2014) in a recent review of online exercise sites found the use of self-regulatory mechanisms for goal setting (41.3%) and provision of feedback (46%) was relatively low given the amount of evidence supporting the use of these features in effective health change interventions in the offline world. This study did not determine the types of feedback provided by these sites by way of distinguishing normative and [11]ipstative feedback. Understanding the presence and levels of operationalised normative and ipstative feedback in exercise sites may go some way to better identifying how effective these sites may be in using feedback mechanisms to encourage exercise self efficacy. The *thumbs* function in conjunction with exercise planning and comparison of exercise efforts and outcomes illustrated by visual analytics could be a step in the right direction to providing users an opportunity for greater self-regulation, feedback and self-affirmation.

The *shouts* function, fits into the interaction graph concept as explored by (Long et al., 2013) and affords the movescount.com user the opportunity to comment to another user, using the system. This is a far more active engagement with the system than simply indicating a *thumb*, as it requires greater effort; typing a comment

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[11] **ipsative feedback** is based on providing information on how a person is performing compared with his own previous results, (Enwald, Herzig, Huotari, & Oinas-Kukkonen, 2013)

as opposed to simply clicking on a *thumb* action. The analysis of the population sample revealed that a relatively small number of users make an average of 4.5 shouts each to a larger group of receivers who receive an average of 1.9 shouts each. Each of these distributions was extremely positively skewed, as is evidenced by more than half of the users making and receiving only one shout. This very modest use of the function was echoed in the survey of the population subset conducted in study two. Here, we found that despite at least 75 percent of the respondents regularly using the digital exercise tracking device and logging into the system and uploading a move, in terms of their remaining uses of the system (following another user, shouts, thumbs, joining a group), no more than 25 percent of users regularly or frequently engage in these activities, i.e., at least 75% of respondents report never or only occasionally engaging in these activities. Of the possible uses of the device, the most popular when ranked by the mean is following another user (M = 1.55, SE = 0.03), followed by joining a group (M = 1.44, SE = 0.03). Again using the mean as an indicator of popularity, the least popular other usage of the device is adding a shout or comment to another user's move or to a group. Both the Number of General Shouts Made and the Number of General Shouts Received are moderately positively correlated with Login Count at less than a 0.001 level of significance, although the correlation is only 0.30 for General Shouts Made and 0.39 for General Shouts Received. This result is to be expected, as the user needs to make the effort to login in order to make a *shout*. A stepwise regression of the Number of General Shouts made on Login Count implies that on average about one additional shout is made for each four additional logins.

Regression analyses also determined that neither gender nor any of the anthropometric measures including BMI and self-reported Fitness Index were associated with the number of general *shouts* made by users; where general shouts are online comments made from one user to another but not directed at an uploaded exercise session. Descriptive analyses of *shouts* that were directed at the *moves* of other users indicated that 1,467 users received shouts, with an average of 3.5 shouts received by users. As well, 3,913 different moves received shouts with a move receiving 1.3 shouts on average. Of the 1,467 users that received shouts, each user received shouts during 2.6 moves on average. Interestingly, better scores by users on the fitness measures, Minimum of Fitness Index and Median of BMI, are associated with an increased Number of Moves Receiving Shouts for that user as is the Number of Moves. On the face of it, the fitter, leaner users exercise more using the system and receive more shouts from other users. To somewhat underline this phenomenon; in terms of the median of BMI, each increase of 4.5 to BMI leads to an average of one fewer moves-receiving shouts. There is insufficient evidence to speculate as to the reasons for why these less lean individuals receive less interactive comments from others around their uploaded exercise efforts in this system. In terms of gender differences, in our sample, 340 males have an average of 2.9 moves that receive shouts, whereas 32 females have an average of 4.9 moves that receive shouts. On the face of this data, it seems that female users garner more comments about their exercise uploaded to the system than male counterparts. Kimbrough, Guadagno, Muscanell, & Dill (2013) found, in an analysis of online behaviour that women, compared to men, are generally more frequent mediated communication users. Compared to men, women prefer and more frequently use text messaging and social media. In a survey-based study of the text messaging experiences of one hundred and fifty three 18 to 24-year-old students, it was found that women, compared to men, are generally more frequent mediated communication users, (Ceccucci, Peslak, Kruck, & Patricia, 2013). Compared to men, women prefer and more frequently use text messaging and social media. This may not only explain the gender differences in the propensity to generate *shouts* made at *moves* in movescount.com. However, it's important to recall the relatively low usage of online social interaction functions shown by the surveyed sample of users in study two which were overwhelmingly male.

In seeking to better understand the nature of online relationships and their relative strengths, particularly as they reflect offline or real-world ties between individuals, (Wilson et al., 2009) and (Viswanath, Mislove, Cha, & Gummadi, 2009) used the level of interaction between users using key Facebook functions such as posting on another's "wall" to distinguish strong from weak links online. Viswanath et al., (2009) analysed the Facebook interactions of over 60,000 users, with wall post data from September 26th, 2006 to January 22nd, 2009. They observed 838,092 wall posts, for an average of 13.9 wall posts per user, spanning communication between 188,892 distinct pairs of users, representing 12.2% of the links in the social network. The remaining 87.8% of the links in the social network did not exhibit any wall activity. This small portion of users exhibiting low wall activity is consistent with our findings for *shouts* amongst users of movescount.com where of 20,000 users only 1,467 or 7.33% received *shouts*. The same study also found that links in the activity network tend to dwindle or deprecate over time, and the strength of ties exhibits a general decreasing trend of activity as the social network link ages. For example, only 30% of Facebook user pairs interacted consistently from one month to the next in their population sample. This online social tie entropy is a possible area of further investigation for digital exercise tracking systems particularly if it can be assessed in terms of its association with exercise persistence across extended time periods.

In terms of *moves*, the Number of Moves and Login Count have a moderately strong correlation of 0.44, which is statistically significant ($p < 0.001$). The correlations between system use indicators, Login Count and Number of Moves, with the metrics of exercise intensity (Heart Rate Average, Training Effect and Calories Expended) show only weak positive correlations. It is apparently not the case that the count of Logins or Number of Moves is associated with exercise intensity variables to any large extent. Interestingly, the system-determined exercise intensity-outcome measure known as Training Effect (TE) is associated with a decrease in Login Count, with every 1-point increase in TE implying -3.9 (SE = 0.637, $p < 0.001$) additional logins. The TE value (which ranges from 1-5) refers to a personal training effect, a method that takes heart rate readings over the duration of the exercise and calculates relative intensity based on how closely actual exercise heart rate approximates maximal heart rate. This measurement is similar to the heart rate training zones used in clinical testing to calculate for an athlete following a maximal exercise test except that maximal heart rate in this instance is assumed. The TE value that is attained is then used to calculate the recovery time variable and incorporates user profile setting variables such as age into its calculation. The exact algorithm was not made available by the vendor for further scrutiny.

The negative association between high TE values and Login Count may occur because the more intense an exercise session is and the greater its TE, the less the number of such sessions would likely be completed over a given time period such as a training week and the greater the rest or recovery needed between sessions. It is established that both time and intensity of peak workloads are pivotal for the level of acute physiological responses to intermittent exercise, (Tschakert et al., 2015). In addition, the nature of the recovery portion itself by way of applied intensity and duration plays an important role. Calibration of recovery portions affects VO_2 levels through these portions and determining the time taken by an individual to hit peak VO_{2max} values in subsequent peak-workload phases, (Tschakert & Hofmann, 2013). As well, it is known that peak training workloads can lead to neuromuscular fatigue and deprecated subsequent exercise quality, (Buchheit & Laursen, 2013). Both HrAvg and Calories are positively correlated with Login Count. A 10 beat per minute increase in HrAvg implies 1.7 additional logins ($p < 0.001$) and a 100-calorie increase in workout intensity implies 0.6 additional Logins ($p < 0.001$). Taken in isolation, it is difficult to speculate as to why this occurs other than to say it may be consistent with the earlier discovery from our study that users who are fitter (by way of self-reported Fitness Index scores), complete more strenuous exercise sessions and reveal lower BMI scores and login more often to the system.

The propensity for a portion of users to publish their movescount.com moves as tweets on Twitter is associated with substantially higher levels of logins and uploaded moves to the movescount system; the estimated coefficient on Publish to Twitter suggests that users of Twitter have 5.1 moves more ($SE = 1.435$, $p = < 0.001$) uploaded to the system than users who do not Publish to Twitter and a similar regression analysis reveals that the online social behaviour of Publish to Twitter is positively correlated with Login Count. Users who Publish to Twitter have an average of 13.2 more logins ($SE = 2.857$, $p < 0.001$) than people who do not Publish to Twitter. This was a totally unexpected finding and may be of significance for designers of digital exercise tracking systems and allied health practitioners looking to use the technology, particularly if subsequent investigation can ascertain how and why the ability to publish tracker exercise data to Twitter boosts exercise regularity. Also from study two, this extraordinary group of users who published their exercise sessions to Twitter demonstrated significantly higher ROPAS scores (*M* = 3.84, *SE* = 0.10) than the users who don't publish (*M* = 3.56, *SE* = 0.09).

From the literature, (Wilson & Bengoechea, 2010) in assessing the validity of the ROPAS scale found that amongst the 522 participants in their study higher ROPAS scores were associated with greater perceived autonomy and competence and greater well-being. Standage et al., (2012) found that amongst secondary school students, relatedness to others in physical activity predicted health-related quality of life outcomes. It may be that those movescount.com users that publish their moves to Twitter are autonomous in their motivation for exercise, enjoying greater competence and wellbeing. Determining greater proof for this possibility would require a follow up study using standardised SDT scales to accurately assess the measures of motivation, perceived competence and wellbeing within the context of pre and post usage of the system over an extended period of time.

Social Activity

In our investigation of social activity online, users in the population were assessed for their group membership. From the source file of 23,449 users were found to belong to 1,046 groups. Group sizes have an extremely long right tail, with 90 percent belonging to groups of less than 80. Average group size is about 46 members with more than half of the users belong to only one group and more than 25 percent of the users belong to at least two groups. The correlations between Login Count and Number of Groups Joined is 0.31, and the correlation between Number of Moves and Number of Groups Joined is 0.13, both of which are statistically significant at less than the 0.001 level of significance. This implies that logging in to view or participate in group-based online activity may be a reason for user system engagement. It was also found that more males join groups than females who use the system. Group formation online such as this is an instance of similarity driving connection or homophily. Personal social networks are homogeneous with regard to many sociodemographic, behavioral, and intrapersonal characteristics, (Mark, 2003). McPherson et al., (2001) believed that homophily influences information content received, formation of attitudes and the nature of interactions. There is evidence that users in online social networks tend to align with similar others in a process known as assortative mixing (an instance of homophily) and that users of Twitter exhibit subjective wellbeing (SWB) based on their assortative mixing, (Mcauley & Leskovec, 2014). Centola (2011) found in an experimental study that homophily significantly increased overall adoption of a new health behavior. Little by way of conclusion can be drawn from the analysis done in our study that resonates with the literature other than that group-membership is prevalent across the population with the individuals joining two groups on average. The system does encourage users to congregate around homophilous attributes with sports events, activity types and group location operationalised as group set-up functions. What can be said is that the group function on the system is well frequented by a significant portion of the user population and this contributes to login count. The mechanics of the movescount.com system and its datasets could lend itself to an investigation into behaviour change and information diffusion across homophilous groups. This may allow a more detailed understanding of the role of homophily on exercise outcomes and persistence.

A crucial driver for the study has been the desire to determine how persistently individuals engage with the system over time in light of the finding that one third of all adult Americans who use a wearable sensor device for activity tracking abandon use of the system after six months; (Ledger & McCaffrey, 2014). *Persistence* as a measure here in our study is defined as a user having at least one move within 60 days of the end of the file cut-off date of January 20th, 2013. A classification and regression tree analysis (CART) was conducted to find groups of attributes that classify users as either *persistent* or *not persistent* by our definition. These were a cross section of attributes that represented a number of possible variable bundles able to provide an indication of system-specific online sociability and fitness measures. The analysis revealed that regardless of other attributes, males in the highest quartile of Average Fitness Index and females in the highest quartile, except for the youngest females (i.e., under 30 years old), persistently exercise. Additionally, the majority of people who are in the top 50 percent of the Average Fitness Index persistently exercise regardless of their online sociability inside and outside of the movescount.com system. In the tree it was found that for users in the first and second quartile of Average Fitness Index who do not have the most intense moves (lower TE scores), but Who Have Followers persistently work out. For users who are in the lowest 50 percent of Average Fitness Index, that do not have the most intense workouts and have no Followers, but who have a Twitter account persistently work out with the system. This finding may have an association with the subsequent analysis done in study two that used a psychosocial scale incorporating a measure of relatedness to others in physical activity (ROPAS) to discern the relationship between a user's score on this measure with their use of the social support features of movescount.com.

It may be implied, subject to further investigation that high ROPAS scores could be associated not only with the tweeting of exercise data but for the less fit, (based on the movescount system's scoring methods for this measure) it may positively influence their persistence with using the device for managing their exercise over a longer period of time. This inference is illustrated in Figure 46 and requires challenge.

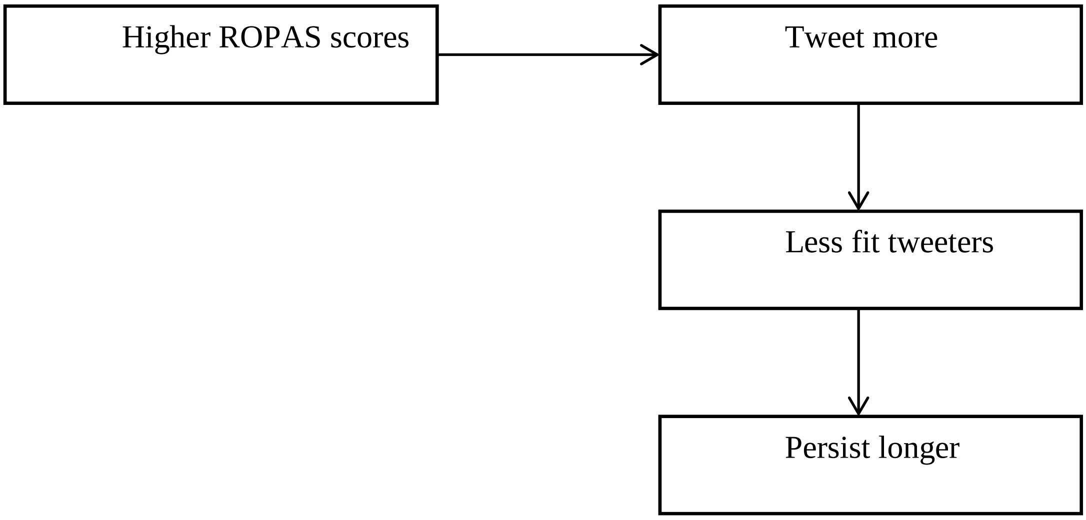

Figure 46. Relatedness to Others in Physical Activity Scores (ROPAS) and an inferred association with tweeting by less fit users and their persistence with the device for exercise.

In summary, in an active population sample of individuals using a digital exercise system there is a tendency for younger, fitter males to persist with exercise and continue using the system. In relating this finding to the SDT literature for exercise, it may be that the most persistent members of the population sample possessed high levels of autonomous self-regulation, intrinsic motivation and perceived competence, (Teixeira, Silva, et al., 2012). In examining the intention to continue in sport amongst young adults, (Gucciardi & Jackson, 2013) found that positive attitudes stemming from satisfaction of basic psychological needs and perceived behavioural control predicted sport continuation. In hindsight, use of a more extensive set of scales for determining the levels of each of the BPN needs for individuals in the population sample may have helped to determine the potential role of the satisfaction of each need in persistent use of the system for exercise.

The second, qualitative-based study primarily focused on the persuasive elements of the *movescount.com* system as elicited from the BCSS-PSD theoretical framework used to design behaviour change systems. Additionally, an insight into a little more demographic detail and exercise and system usage regularity of the surveyed population subset was completed. About 92 percent of the respondents were male and slightly more than three-quarters of the respondents were either married or had a domestic partner. They are a well-educated group, as more than half (53%) have at least some graduate school experience and more than 96 percent graduated high school. The mean age as of January 1, 2014 was 40.32 years old, with a standard deviation of 9.69 years and a range of 17 years old to 69 years old, consistent with the results from the first study. More than 85 percent of the sample (445/521) had exercised in the year preceding their purchase of the device. Of the 75 people who had not exercised in the year prior to purchasing the device, 80 percent had exercised at some point in their lives. Clearly, our survey sample was consistent with the database population used in study one in terms of their engagement in physical activity. At least 75 percent of the respondents reported regularly wearing the device, logging into the system and uploading an exercise session (move). They seemed to see the device as compatible with their exercise regimes. In the structural equation model constructed, the variable "were you exercising before (purchase of the device)" has a direct effect in lowering a user's perception of the overall features of the system. As a result these users displayed somewhat less positive perceptions of the effort needed to use the system, its overall credibility and a somewhat lower intention to continue using the system. However, it’s important to note that a chi-square test of whether a user intends to continue or not based on whether they were exercising in the previous 12 months indicates that these two variables are independent.

The survey itself was a composite of an existing measurement instrument originally devised to investigate intention of use continuance for web sites providing weight-loss management, (Lehto & Oinas-Kukkonen, 2013), the Relatedness to Others in Physical Activity scale (ROPAS) originally published by (Wilson & Bengoechea, 2010) and a sub-scale for Online Sociability from (Johnson & Kulpa, 2007). The original ROPAS scale was designed to indicate the degree to which exercise is a social activity for an individual in a real world physical setting only, without any attempt to connect that to Internet usage. The current study looked to link ROPAS with user patronage of key online social functions of the movescount.com by examining the association of user ROPAS scores with the two key BCSS-PSD design constructs of Social Identification and Social Support as implemented in the system. The Online Sociability (O_SOC) scale used indicates usage of the Internet for communications such as email and meeting with others, but does not reflect sophisticated use of social media such as Twitter, YouTube or Flickr and is not directly related to exercise. It was included in the survey to determine at least a level of moderate familiarity with and usage of the Internet for social purposes by movescount.com users. Both of these additional scales were treated as single factor scales. It was reasoned that BCSS is in an embryonic stage of development as a theory of systems design and its existing evidence base accrued through application of its current measurement scale was largely confined to the weight loss and alcohol control problem domains. It was considered that validating the BCSS scale against a digital exercise tracking system constituted reasonable analytic practice. In terms of re-using validated instruments, particular in the area of systems design and assessment, it is believed to be a sound and efficient method for improving the existing knowledge base and facilitating viable study comparisons, (Boudreau et al., 2001).

The original BCSS instrument used an eight factor scale to cover the key PSD categories of (i) CONT or use continuance, the intent of the user to keep using the system; (ii) CRED or systems credibility based on the user's perception of the system's trust, reliability and believability; (iii) (DIAL) or system dialogue support for the user, which should take the form of feedback, prompts, suggestions and reminders to keep the user on task; (iv) (EFFE) or the perceived effectiveness of the system in assisting the user to perform key tasks; (v) (EFFO) the user's perception of how much work is needed to use the system effectively; (vi) (PRIM) or primary task support is the user's judgment on how well the system supports the user's achievement of goals through facilitating goal setting and tracking, adapts to user's needs and promotes the user's self-efficacy; (vii) (SOCS) or the perceived social support the system affords the user in helping them reach their goals and (viii) (SOCID) or social identification is an assessment by the user of how well they identify with other system users and the extent to which they share interests and feel part of a user community. The factorial analysis conducted mirrored results largely similar to the original work which found for weight loss management web-based system the intention to continue using (CONT) is determined by users' perceptions of the effectiveness of the system (EFFE), the effort required to use the system (EFFO), the credibility of the system (CRED), and the social support offered by the system (SOCS). In turn, perceived effectiveness (EFFE) of the system and the perceived effort required to use the system (EFFO) are functions of primary task support (PRIM). From our study we observe that there are especially strong correlations between SOCS and SOID ($r = 0.745$, $p < 0.001$), PRIM and EFFE ($r = 0.625$, $p < 0.001$) and PRIM and DIAL ($r = 0.641$, $p < 0.001$) and DIAL and EFFE ($r = 0.592$, $p < 0.001$). PRIM and CRED are also correlated at more than the 0.5 level. In the sample there is overwhelming support for the same positive relationship between the scales for PRIM and EFFE (B = 0.825, $SE = 0.052$, $p < 0.001$) and PRIM and EFFO ($B = 0.419$, $SE = 0.044$, $p < 0.001$ as has been found with weight loss management systems, (Lehto & Oinas-Kukkonen, 2013). This is an encouraging endorsement of the original BCSS measurement instrument and may indicate that it has application to the assessment of the persuasive design category associations in digital exercise systems such as movescount.com

It's at this point that our factor analysis with its inclusion of the additional ROPAS factor shows a fresh divergence from the literature and the emergence of an interesting association. Regression coefficients for the regressions of the scales of SOCS ($B = 0.165$) and SOID ($B = 0.187$) on ROPAS respectively revealed a statistically significant positive relationship. Although, high scores on the Relatedness to Others in Physical Activity Scale (ROPAS) predicts high scores on perceived social support (SOCS), ROPAS is not specifically related to any exercise data system or online social network so much as it is a reflection of face-to-face contact during exercise. As a result it was reasoned that social identification with an online community that uses the device might be a prerequisite for ROPAS to have any effect on social support. This triggered an investigation of the hypothesis that users' social identification scores (SOID) can mediate the relationship between ROPAS and SOCS scores. Following mediation analysis, ROPAS was found to have a significant effect on SOID scores, $B = 0.653$, $SE = 0.034$, $p < 0.001$. Further mediation revealed that the significant effect of ROPAS disappears after SOID is added to the model.

Observe that SOID fully mediates the relationship between ROPAS and SOCS scores underscored by results of the hypothesis test recommended by (Sobel, 1982) that confirms the significant mediator effect of the SOID, $z = 3.340$, $p < 0.001$. It appears that for an individual who perceives high levels of relatedness to others during physical activity in the real world and identifies strongly with the online community of fellow digital exercise tracking users they will likely feel they receive high levels of social support from the system. This ROPAS associative behaviour dynamic and the other observations from the online activities of participants are depicted in Figure 47. Interestingly, from the structural equation model it appears that although joining a group online is an indicator for a statistically signficantly higher value of online sociability (O_SOC), an increase in age and being single shows statistically signficiantly lower ROPAS. This implies that as users age and live as singles their relatedness to others in physical activity declines and with it a propensity to engage with the systems social support functions.

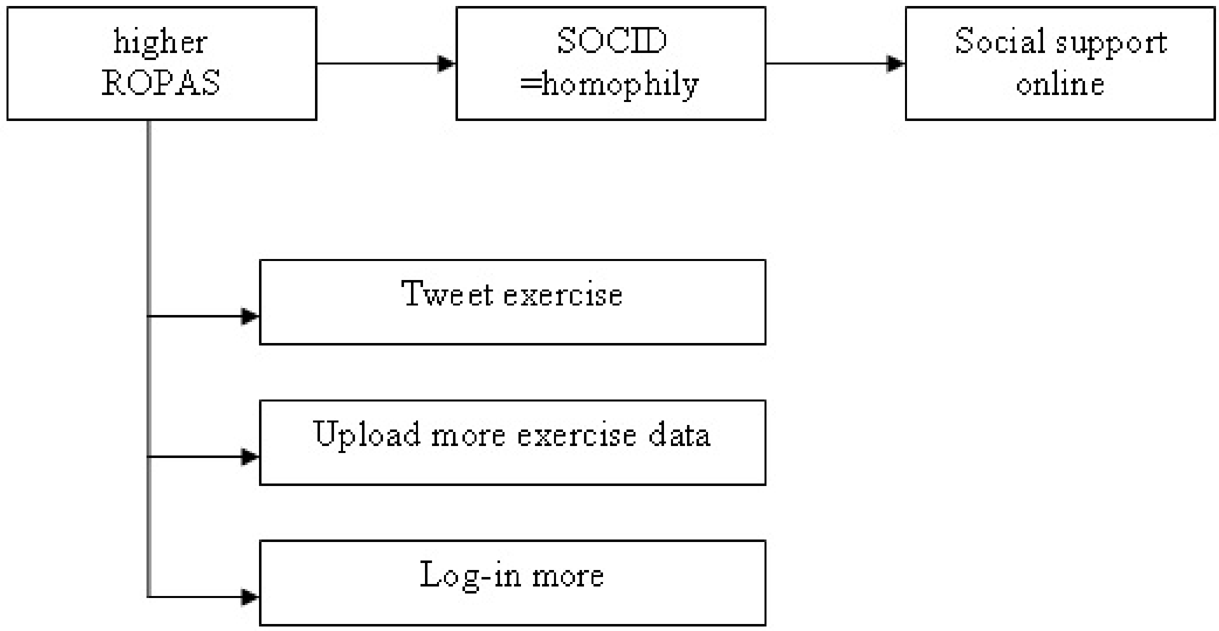

Figure 47. Relatedness to Others in Physical Activity Scores (ROPAS) and its association with the elements of the PSD Design Category Social Support and systems interaction frequencies of movescount.com

These strong associations between social needs satisfaction, systems usage and exercise frequency prompted further analysis of the scale data. It emerged that a surprisingly large number of users who at least report no external social media accounts in their exercise profiles but are active users of the social networking features of the movescount.com system exhibited significantly higher values of ROPAS, SOCS and SOID than other survey respondents and also seem to find the system easy to use. These findings triggered the third study; an effort to ascertain a view on how much of an idealized BCSS-PSD feature set coverage has been implemented by movescount.com as a persuasive system aimed at encouraging exercise behaviour. This was done using a previous subjective assessment scale, (Lehto & Oinas-Kukkonen, 2010) and making use of a small panel of experts in BCSS-PSD application to real-world systems design and development across health applications, (de Jong, Wentzel, Kelders, Oinas-Kukkonen, & van Gemert-Pijnen, 2014). It was a difficult task to recruit more than a handful of appropriately qualified and experienced panellists resulting in a smaller than preferred sample size. As a result, the findings are not overly definitive and can be best regarded as a guide only to understanding the relative persuasiveness of the movescount.com system. Of the key BCSS-PSD recommended design elements, the system scored most strongly in the areas of Primary Task Support (PRIM) and Social Support (SOCS) but was found wanting in sub-categories of both and overall was average in terms of its operationalization of Dialogue Support (DIAL) and Systems Credibility (CRED). The low scoring for the Reminders and Suggestions design variables may warrant attention from the vendor as these tools are often represented in web and mobile-based support apps targeting exercise adherence and may be effective in that regard, (Brannon et al., 2013). Similarly, the relatively poor implementation of Simulation and Rehearsal is disappointing in terms of behavioural support for exercise persistence as both may encourage goal management, self-regulation and perceived competence (Bar, 2011; Oettingen, 2012). Given the breadth of the system itself, a full manual of its use has not been included with this study and instead a summary of the panel expert findings are provided in **Appendix G** affixed to those systems function screens most closely aligned to BCSS-PSD design categories.

The strong rating for SOCS functionality is consistent with the findings in the first two studies in this thesis. The low ratings for the Competition and Recognition persuasive design elements in this category may warrant review of systems functionality by the vendor. While there is no substantive evidence to demonstrate the role that an online exercise systems deployment of competition functionality may have to positively influence persistent use of the system for exercise, there is some evidence that head to head competition in real world athletes using technology does improve performance. Corbett, Barwood, Ouzounoglou, Thelwell, & Dicks (2012) working with track cyclists assessed individual performance in completing 2000m time trials using a virtual race screen mimicking real world competition with the result that participants exceeded previous best performances. There is however no corresponding work to suggest that athletes competing against one another with their athletic performances published online tend to use the system that enables them to do this more persistently and exercise to any lesser or greater degree as a result of using such a system feature. In the emerging field of gamification, defined by Deterding, Dixon, Khaled, & Nacke, (2011), as “the use of game design elements in non-game contexts” (p1.), use is made of competition and recognition elements in apps designs in order to encourage more regular use, including health and exercise apps such as NIKE PLUS and Fuelband®. Yet, in a recent review of 132 health apps Lister, West, Cannon, Sax, & Brodegard, (2014) examined the correlations between health behaviour constructs, gamification and game element and found a failure to integrate elements of behavioural theory into the apps. Clearly, there is a significant gap between behavioural theories and their adequate implementation in health and exercise apps in general, with the movescount.com being construed as a partial implementer of these theories. Case,Burwick, Volpp, & Patel (2015) also point to the lack of engagement strategy around these apps and systems with the key factors of collaboration and feedback, necessary in the context of the health behaviour change target itself, the behaviour change environment and its stakeholders. In effect, the technologies tend to operate in isolation from the true care and support environment.

The relatively poor DIAL and CRED ratings indicating there may be room for improvement by the systems designers in better dialogue-based interaction with users. It's important to understand that the movescount.com system as shown in Figure G5 in Appendix G provides an extremely comprehensive exercise performance and planning function which would satisfy most expert users' assessment of operationalization of self-regulation as shown by the results in study three. From a first person user perspective, the system allows fully for feedback on individual exercise effort in fine detail but it's goal setting and management functionality is based entirely around planning of exercise sessions and is entirely divorced from personal goals which may go some way to explaining the mixed appraisal it received for its self-regulatory elements from the panel. The low CRED ratings by the panel attest to the belief by experts that the system lacks sufficient third-party endorsement and verifiability in particular, according to the original definition of each of the CRED category features. These ratings and the original definition of the CRED measure do not however take into account the extensive library of third party and user-designed apps that use the movescount.com platform to extend the functionality of the Suunto software ecosystem to the broader user population. Currently, in addition to the nineteen commercial third party apps, the movescount.com user community provides almost five thousand user-designed apps of which seventy-two have more than one thousand users each.

The movescount.com system is in effect a technology *platform* a standardised technology infrastructure comprising development standards, processes and support that enables it to be accessed by developers external to the original vendor that provide functional extensions and external integrations through their own software. The *Fitbit® and Nike Plus® activity* tracking systems likewise enable the ready integration of third party apps and online services. Platforms particularly if managed as an open environment, encourage innovation, information diffusion and growth, (Allen, 2012; Boudreau, 2007). The authors of BCSS could perhaps consider revising their definition of systems credibility (CRED) to include an item for the interoperability and extensibility of persuasive systems as measured by the number of first, third party and user community applications created and used. Surely, any systems capable of engendering sufficient trust in its users and third part industry suppliers to create such a large and well-patronized supply of apps demonstrates high levels of credibility.

This study, by uncovering potentially interesting and valuable observations of a digital exercise systems' influences on the exercise behaviour of its users may have helped bring into focus the need for software engineers, architects and business analysts to better embrace traditional health behaviour models and newer persuasive systems design theories. Harjumaa & Muuraiskangas (2013) investigated how the PSD model was used in the development of new functionality in two heath and wellbeing BCSS apps, particularly in relation to its incorporation into an agile software development methodology. They found that this incorporation resulted in the discovery of additional persuasive functionalities in the analysis and design phase. Similarly, (Alahäivälä, Oinas-Kukkonen, & Jokelainen, 2013) successfully used the PSD model to architect, develop and implement a weight loss management system. These two instances are scant evidence but represent tangible progress in the application of the PSD model to BCSS. The current study, through the panel expert analysis, shows perhaps a popular BCSS like movescount.com could produce better persuasiveness for exercise with a more extensive implementation of the PSD model. Certainly, the Suunto platform is not the only online health and wellbeing system that could benefit from inclusion of health behaviour and systems persuasiveness theories as found by (Vandelanotte et al., 2014) in a systematic review of evidence-based and social media tools in PA intervention websites. The sites under review could only muster an average Behavioural Components Score of 3.45 out of 10 and an average Interactivity Score of 3.57 out of 10. However, the same sites were incorporating social networking functionality via Facebook (65.2%), Twitter (47.8%) and YouTube (47.8%) to indicate some intention to use social support and social facilitation around PA interventions.

It is the encouraging signs of association between Twitter publications of exercise moves; device persistence and move upload regularity found in study one that triggered the investigation for study four. This study looked to discern if there was anything particular about the exercise behaviour, type of activity, and use of additional exercise tracking and publication devices of a sample of those movescount.com users that Tweet their moves. It also looked to determine the role, if any, played by the online social influence score of these individuals as measured by the *klout.com* service on their exercise behaviour.

There was very little of significance to emerge from the analyses of the users, their exercise tweets, activities, exercise outcomes and online social influence scores. Individuals that are involved with canoe, kayak and motor sports exhibited substantially higher KLOUT scores on average compared to the rest of the sample population of 656 unique Twitter handles, with 562 males (85.67%), 37 females (5.64%) and 57 (8.69%) of those whose gender could not be identified. In terms of physical activity duration, the middle 50 percent of the distribution works out from roughly 45 minutes to 90 minutes for both men and women. From a regression analysis, neither KLOUT scores nor gender appeared to be significantly associated with distance covered in a move, once activity is controlled for. An individual's estimated online social influence has nothing to do with how far they cover in an exercise session that they choose to publish to Twitter. Similarly, a probit regression of KLOUT scores, use of another device and exercise outcome (intensity) could not show that those who have higher online social influence somehow workout more intensely.

There is some evidence that Males have an average KLOUT score that is lower than Females, with the point estimate of average male score being the average female score minus 4.719 (*p* value 0.059). None of the Move indicators, Speed, Distance, or Duration, has a statistically significant effect on KLOUT score. The two variables that have significant effects on KLOUT score are Number of Followers, with a point estimate of an increase in average KLOUT score of 2.91 for each additional 1,000 Followers, and number of Tweets, with a point estimate of an increase in KLOUT score of 0.838 for each additional 1,000 Tweets. This is consistent with what evidence exists in the literature which points to both these variables likely being incorporated into the KLOUT score algorithm, (Nguyen & Zheng, 2014;Campo-Ávila et al., 2013).

There is nothing out of the ordinary about the exercise behaviour of the Twitter sample examined nor can any association be made between the online social influence scores of these individuals and any measure of their exercise outcomes. Perhaps, more value could be attained by running a qualitative survey of these users to determine key psychosocial traits including personality type for exercise and online behaviour including social influence as well as assessing their PSD element usage as carried out in study two. The goal from this suggested research would be to determine what it is about this cohort that sees them use their digital exercise tracking system with comparatively greater regularity.

Other considerations

This thesis is constrained by the nature of its source data. It is also constricted in scope by the limited number of selected health change behaviour and persuasive systems models used as its theoretical framework. These and other delimitations, assumptions and limitations to the project scope and conclusions are explained as follows.

Assumptions

1. The only means by which an individual can access and use the movescount.com system effectively is to have purchased an exercise-tracking device from Suunto such as the AMBIT series smart watches. It is assumed there has been no fabrication of source data from non-registered users and devices. It is also assumed that any Suunto systems development that generated company specific test data was removed from the data sources for the project prior to data transformation for this project.
2. The accuracy, integrity and reliability of the exercise measurements gathered by the Suunto wearable devices including heart rate monitor are assumed to be satisfactory.
3. The error trapping and data validation functions of the movescount.com system are assumed to be effective in preventing erroneous data from being entered by users of the system.
4. The respondents to the survey instrument used in study two are assumed to have answered the survey questions honestly and accurately.

5. The responses from the panel experts in study three are assumed to have been free of pre-existing biases and to be honest and accurate.
6. Any self-reported values recorded by individual users of the system are assumed to be a reasonably accurate representation of that individual's assessment of the value in relation to their physical state and exercise effort.
7. It is assumed that the randomised cross section of the total user population the study uses includes one or more Suunto-sponsored athletes that will have a larger number of followers. These individuals are assumed to have significantly more frequent uploads and exercise outcome values above the population mean.

Limitations

1. The population sample of 20,000 individuals used as the basis for the research study represents a randomly selected 5% subset of the current approximate total population of users of the movescount.com system as at the date of commencement of the data transformation stage of this project.
2. The number of respondents to the survey that was sent to a 12,000-member subset of this sample elicited a 4.7% response and the number of members of the union of these user data sets in limitations 1) and 2) was insufficient to conduct a unified assessment of respondents as a single pooled data source.
3. In the absence of an independent means of testing and verification of exercise outcomes, the system generated value for Training Effect (TE) has been used.
4. There was a lack of data pertaining to the relative level of completion of individual user profile information.
5. Similar to the limitation detailed in point 2, logistics and privacy permission control from the vendor prevented the use of moves published to Twitter by

individuals that had membership of the population samples used in studies one and two.

6. The population sample used for studies one and two was sourced from the one systems vendor, Suunto Oy of Finland only. Data from similar systems vendors including NIKE and FITBIT were not made available to the researcher.
7. Similar to point 5) the same restrictions made it impossible to trace the publication of movescount moves to user Facebook accounts.

Delimitations

1. The potential scope of the theoretical aspect of the investigation was limited effectively to the SDT and its Basic Psychological Needs (BPN) mini theory, the Behaviour Change Support Systems (BCSS) theory and the factor known as Relatedness to Others in Physical Activity scale (ROPAS) that is a core element of the Basic Psychological Needs Theory (BPNT). Greater breadth and depth of findings may have been possible by including validated qualitative instruments for assessing an individual's perceived competence for exercise and their level of autonomous motivation in addition to ROPAS. Instruments for these and other SDT measures would provide a more extensive assessment of the role of *complete* BPNT needs satisfaction on exercise behaviour and systems use. The ROPAS delimitation did however serve to narrow focus to the social interaction associations in the real world and online in the digital exercise system under investigation. The delimitation choice for ROPAS was based on the prominence of the online social networking functionality in the system used particularly as drawn from the results in study one and the dearth of existing evidence examining it.

2. The nascent state of development of the BCSS-PSD model for persuasive systems design necessitated use of an existing measurement instrument but in breaking new ground, it was applied to a different population; active athletes versus weight loss. This was seen as a means to confirm, through contest with a different population in a related problem domain, the initial validation work in the literature.
3. The need to evolve the instrumentation of the PSD model as a means for assessing a digital exercise systems' persuasiveness in affecting continuation of existing exercise behaviour led to the incorporation of the ROPAS and O_SOC scales into the BCSS-PSD survey instrument. Accomplishing this may mean the instrument gains broader applicability to linking online and offline social behaviour analyses in systems similar to movescount.com.
4. It's feasible that the project findings could allow others to generalize the conclusions and apply these to populations of users of similar activity tracking systems although it's recommended further work be done with these additional data sources to confirm commonalities and identify differences.
5. Although the project drew on a pre-randomised sample of movescount.com users these proved to be predominantly male as were the subset sample of survey respondents. It may be less reasonable to generalize from the project findings for the global population of female digital exercise tracking systems users. It is recommended that any additional work address this through examination of alternate activity tracking data sources including female-targeted products such as *misfits®.*

Chapter 8

Conclusions

This final chapter explains the possible contributions to research of the thesis and suggests future directions for related research. Briefly, the thesis has demonstrated the following:

1. It described the characteristics of a large, reasonably representative sample of physically active users of a popular digital exercise tracking system.
2. It described the characteristics of the interactions of this user population with the system itself and with each other online.
3. It identified associations between user anthropometric attributes, and their exercise and online social behaviours.
4. It identified associations between system usage behaviours, the anthropometric attributes and exercise outcomes of users.
5. It determined that a tendency for those users that followed the activities of others using the system reflected itself in more frequent system usage.
6. It identified and classified the users' persistence for exercise using the system according to key anthropometric and behavioural attributes.
7. It identified a proclivity for greater system usage from those users that chose to publish their uploaded exercise sessions to Twitter.
8. It found that the fitter, leaner users exercise more using the system and receive more shouts (online comments) from other users.
9. It was discovered that more than 25 percent of the users belong to at least two online groups in the system under examination although there was insufficient data to establish causality through homophilous user profile attributes.

10. It was discovered that a majority of users made use of the system's *thumbs* function to signify self-affirmative contentment with uploaded exercise sessions.
11. It discerned a positive association for the less fit users between their Twitter usage and their persistence for exercise using the system.
12. It establishes that with a surveyed subset of individuals from the user population they are overwhelmingly male (92%) and active in exercise with more than 85 percent of the sample having exercised in the year preceding their purchase of the device.
13. It found that at least 75 percent of the respondents in the survey sample reported regularly wearing the device, logging into the system and uploading an exercise session (move).
14. It discovered that of the possible social interaction uses of the device, the most popular was following another user, followed by joining a group with the least popular other usage of the device being use of the shout functions of the system.
15. It established that a system's effectiveness is strongly driven by its ability to enable users to complete primary tasks such that the effort required to do this is perceived to be not insurmountable by the user. This is consistent with the persuasive systems design theory known as BCSS and existing evidence.
16. It showed that users of the activity tracking system believed the effort required to use the system effectively strongly influenced their decision to intend continuing using this system. This is consistent with the existing evidence based on application of BCSS theory to other problem domains.

17. It demonstrated the use of an integrated, psychosocial measurement scale that combines the existing constructs used by BCSS theory to analyse the persuasive elements of a behaviour change system with standardised scales for assessing an individual’s perceived relatedness to others in physical activity along with their online sociability.
18. It discovered using the new hybrid scale that a user’s high score for the desire to be social in exercise predicts high values of social identification in the system, which in turn predicts satisfaction with social support received from the system.
19. It demonstrated that the systems social functions measured by the BCSS scale constructs of social support and social identification with the system does not affect a users intention to continue using directly, but does have a substantial and statistically significant indirect effect through its direct effects on primary task support, system effectiveness and perceived credibility of the system. This is new evidence that contrasts in some small measure with previous work.
20. It demonstrated that in the surveyed sample of users in the target population show a lower perceived relatedness to others in physical activity as they age and are single.
21. It observed that a panel of experts found the activity tracking system under examination to be satisfactory in the persuasive systems design measures (PSD) of Primary Task Support and Social Support but to be functionally moderate only in Dialogue Support and Credibility.
22. It concluded that a group of discreet of users of the activity tracking system that published their moves to Twitter demonstrated no association between

their scores for online social influence as measured by the KLOUT service and their exercise behaviour.

There are also to be concluded implications for designers that create activity tracking systems for health. These are detailed in Appendix L **Implications for Design.**

Suggestions for Future Work

To evolve the potential role of digital exercise tracking systems that positively affect exercise amongst the general population, rather than active athlete cohorts alone, then researchers could look to secure data from users of popular activity tracking systems such as fitbit®, Jawbone®, and misfits® which target those individuals focused on weight loss and wellbeing. A large number of users of these alternate devices to the Suunto *movescount.com* offering buy them to engage in regular exercise as a new or lapsed behaviour and more frequently as a means to augment medical interventions, particularly prescriptive exercise (Cook, Thompson, Prinsen, Dearani, & Deschamps, 2013; Dunne, 2015). If as is supposed, the application of exercise tracking technology to large-scale public health challenges such as obesity is a viable health behaviour change strategy, then the larger and broader the data used in analysis, modelling and planning, the more useful the conclusions are likely to be. To this data, the application of a variety of mixed methods approaches to determine motivation levels and type, systems persuasiveness, the dynamics of online social behaviour and exercise patterns could reap significant findings. There could be greater effort made to determine the presence and role of health behavioural change elements such as self-regulation, perceived competence and autonomy support from SDT and corollaries from equivalent theories including SCM and the Stages of Change (Transtheoretical) Model. More critically, consideration may need to be given to exactly how the design and deployment of activity tracking systems and similar sensor-based services can be improved through the unification of published software engineering and product development methodologies, persuasive systems design models and systems-based operationalization of health behaviour change theories. There exists a good deal of overlap across these knowledge domains. Perhaps an exploration of the best means to unify evidence-based theories such as BCSS, SDT, SCM and agile software engineering methodologies could be a starting point based on large datasets from health and wellbeing vendor systems and a true multi-disciplinary approach. This thesis has show there may be use made of linking health behaviour change measurement scales to persuasive systems design equivalents in order to establish the basic psychological needs satisfaction of users and how this reflects in usage of the system itself. From this, systems designers may better reflect user motivational state with human factor design elements in the system to encourage regular and persistent use and with it, more sustained exercise activity. The successful use of the unified ROPAS-BCSS persuasiveness scale created for this project may warrant further research effort particularly by way of validation amongst similar and related populations including weight loss groups that use popular wearables such as Fitbit®. The application of qualitative measurement instruments for example the Perceived Competence Scale (PCS) and Basic Needs Satisfaction Scale and Motives for Physical Activity Measurement Scale, (Ryan, Frederick-Recascino, Lepes, Rubio, & Sheldon, 1997) in a similar way to which ROPAS has been used here may be one of a number of ways to explore the unification of established health behaviour change theories with emerging systems-based behaviour design models such as BCSS.

Learning more about those individuals that like to publish their activity data to Twitter and why they behave in this manner using standardised personality assessment scales seems a possible extension from the current study. The association between relatedness to others in physical activity and use of online social interaction elements that was uncovered warrants further testing across both different populations and different systems. The area of following behaviour in the social networks of activity tracking systems identified from the current study as a topic of interest, could also be explored further, particularly in relation to the effect of user profile completion on follower numbers and any downstream association with device persistence. Additionally, the phenomenon of a heavily skewed self-affirmative use of a “likes” feedback-function in digital exercise tracking social networks could be tested further with emphasis on the assessment of gradations of satisfaction, causes of this and long term change of satisfaction in line with exercise outcomes and online social behavioural indicators. Extending the investigation into exercise self-affirmation with a view to perhaps better understanding if, how and when users of activity tracking systems assuage and heal their self-esteem through available self-affirmation functions may be valuable. This line of inquiry may help provide more detail on the potential role of digital exercise systems in contributing to stronger and more resilient individual user self-esteem through the uploading and sharing of their exercise data. According to the evidence, the relationships between self-esteem, self-efficacy and exercise outcomes is hierarchical and multidimensional, (McAuley, Mihalko, & Bane, 1997, Elavsky, 2010 and McAuley et al., 2005). Examining the association between systems-based self-affirmation, self-esteem and exercise self-efficacy could be an additional path of investigation.

The nature of social network ties and associations between online social interactions and exercise behaviour may bear further scrutiny in light of the parallel research into social tie deprecation over time in Facebook. Can it be established what affects the lifecycle of online social ties and interactions in digital exercise social networks and the association, if any, with exercise behaviour variables such as frequency, volume and training outcomes? Additionally, the current study has cast light on the possibly positive influence of tweeting exercise data on exercise device persistence for the least fit members of the sample. It could be a worthwhile exercise to firstly determine if this association occurs in other populations particularly amongst those individuals pursuing weight loss. Researchers may like to consider a scalable randomised control trial using identical systems and exercise prescriptions but denying Twitter and similar SNS functionality to one of the experimental groups.

Contributions to the knowledge base

This thesis proffers only moderate incremental evidence worthy of inclusion with the existing base of knowledge. It has generated a thorough description of a population of users of a digital exercise tracking system in terms of their demographic and anthropometric attributes and interactions with the systems and other users of the system. Interesting and potentially valuable conclusions have been drawn about features of the same user population that may influence their persistent use of the technology for exercise.

The strong proclivity for those users of the system that publish their exercise sessions to Twitter in using the activity tracking system more frequently highlights an out-of-the-ordinary behavioural pattern that may warrant further investigation. Validating the existing BCSS-PSD scale for assessing the persuasiveness of a system against a new problem domain may prove valuable for other researchers. Creating and validating a modified version of this scale to examine the association between an individuals social relatedness offline and online in terms of their physical activities may prove valuable in terms of more appropriate application of social support and social identification functions in exercise tracking systems. The decline of relatedness to others in physical activity as users of an activity tracking system age if their relationship status is single may also have implications for design of these systems, pending more extensive investigation across weight loss and health and wellbeing datasets equivalent to those used here.

In terms **of generalising the models** from the thesis to be used by other researchers, Appendix M provides a detailed précis.

Closing Remarks

This thesis was undertaken in response to first-hand experiences with designing and developing exercise tracking systems apps and being frustrated by a lack of evidence-based frameworks for guiding the development process and providing tools for assessing the efficacy of the system in encouraging the intended behavioural change. The investigation was also prompted by the hyperbole surrounding popular digital exercise systems and their positioning as potential silver bullet solutions for tackling the global obesity epidemic. There has been a distinct lack of clear evidence that answers even the most basic of questions needed before considering if and how this technology could deliver on its perceived promise. Who uses these systems? How often do they use them? What kinds of exercise activities are carried out using them? How fit are the people who use them? What happens when an individual's exercise data is uploaded to the closed social networks provided by these systems? How do people interact with one another online? What do the users think of how the system is designed and how does it affect their exercise behaviour and intentions to keep using the system? How persistent are people in their use of these systems?

This thesis goes some way to answering a few of these questions and creating a basic understanding of perceived conceptual gaps found in the design and development of persuasive systems such as exercise trackers. It also demonstrates potential analytic techniques that may be used to elicit answers to the thesis questions and other related inquiries. What it does do is generate more questions than it answers. For example; given the well-established notion that individuals that engage in exercise exhibit varying levels of autonomous motivation and as has been identified here, show varying levels of relatedness to others when exercising surely the user interface and its concomitant functionality needs to adapt to the individual's motivation level and type. The evidential gaps are wide particularly when it comes to the establishment of proof of efficacy and formulation of rules that directly guide the design of the software portion of exercise tracking systems. All this thesis does is attempt, in a very small way. to begin to bridge the gap.

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Appendices

UNIVERSITY of TASMANIA | FACULTY OF HEALTH

Appendix A

Tasmanian Health and Medical Human Research Ethics Committee Approval

03 September 2013
AssocProf Smith
C/- Human Life Sciences
Sent via email

Dear AssocProf Smith

- Application Form – Low Risk
-

The Tasmanian Health and Medical Human Research Ethics Committee considered and approved the above documentation on 30 August 2013 to be conducted at the following site(s):

Please ensure that all investigators involved with this project have cited the approved versions of the documents listed within this letter and use only these versions in conducting this research project.

This approval constitutes ethical clearance by the Health and Medical HREC. The decision and authority to commence the associated research may be dependent on factors beyond the remit of the ethics review process. For example, your research may need ethics clearance from other organisations or review by your research governance coordinator or Head of Department. It is your responsibility to find out if the approval of other bodies or authorities are required. It is recommended that the proposed research should not commence until you have satisfied these requirements.

All committees operating under the Human Research Ethics Committee (Tasmania) Network are registered and required to comply with the National Statement on the Ethical Conduct in Human Research (NHMRC 2007 updated 2009).

Therefore, the Chief Investigator's responsibility is to ensure that:

(1) The individual researcher's protocol complies with the HREC approved protocol.

(2) Modifications to the protocol do not proceed until approval is obtained in writing
REF NO: H0013492
TITLE: A predictive model for determining exercise satisfaction based on sensor-based physiological data and online social networking; a population study.
from the HREC. Please note that all requests for changes to approved documents must include a version number and date when submitted for review by the HREC.

(3) Section 5.5.3 of the National Statement states:

Researchers have a significant responsibility in monitoring approved research as they are in the best position to observe any adverse events or unexpected outcomes. They should report such events or outcomes promptly to the relevant institution/s and ethical review body/ies and take prompt steps to deal with any unexpected risks.

The appropriate forms for reporting such events in relation to clinical and non-clinical trials and innovations can be located at the website below. All adverse events must be reported regardless of whether or not the event, in your opinion, is a direct effect of the therapeutic goods being tested.

http://www.research.utas.edu.au/human_ethics/medical_forms.htm

(4) All research participants must be provided with the current Patient Information Sheet and Consent Form, unless otherwise approved by the Committee.

(5) The Committee is notified if any investigators are added to, or cease involvement with, the project.

(6) This study has approval for 4 years contingent upon annual review. A Progress Report is to be provided on the anniversary date of your approval. Your first report is due 30 August 2014. You will be sent a courtesy reminder closer to this due date.

(7) A Final Report and a copy of the published material, either in full or abstract, must be provided at the end of the project.

Should you have any queries please do not hesitate to contact me on (03) 6226 2764.

Yours sincerely
Heather Vail
Ethics Administrator
Office of Research Services
Email: Heather.vail@utas.edu.au
University of Tasmania
Private Bag 01 Hobart Tas 7001

Appendix B

Study Two Survey Forms

Study Two, Qualitative Survey, Phase 1 Mail out.

* Required Information

Page 1		
* Please enter your 7 digit ID number sent to you by SUUNTO email. (Enter a value between 0 and 9999999)		
______________________________		
Please indicate your gender and date of birth.		
*(a)	Gender (Select one option)	
	◯	Male
	◯	Female
*(b)	Date of Birth	
	_ /_ /__ [mm/dd/yyyy]	

* What is your marital status? (Select one option)	
◯	Married/domestic partnership
◯	Single

* What is the highest degree or level of school you have completed? If currently enrolled, the highest degree you have received so far. (Select one option)	
◯	Never attended school or only attended kindergarten
◯	Grades 1 through 8(Elementary)
◯	Grades 9 through 11 (Some high school)
◯	Grade 12 or GED (High school graduate)
◯	College 1 year to 3 years (Some college of technical school
◯	College 4 years (College graduate)
◯	Graduate School(Advance Degree)

*** Were you exercising regularly in the 12 months before you purchased your device?** (Select one option)

- ◯ Yes
- ◯ No

*** Answer this only if you answered NO to Question 5. Have you ever exercised regularly prior to buying the device?** (Select one option) [Answer this question only if answer to Q#5 is NO]

- ◯ Yes
- ◯ No

The following statements represent different feelings people have when they engage in physical activity. Please answer the following question by considering how YOU TYPICALLY feel when participating in physical activity using the scale provided.

Please evaluate each question below

		False	Mostly false	More false than true	More true than false	Mostly true	True
*(a)	I feel like I have developed a close bond with others (Select one option)	◯	◯	◯	◯	◯	◯
*(b)	I feel like I fit in well with others (Select one option)	◯	◯	◯	◯	◯	◯
*(c)	I feel like I am included by others (Select one option)	◯	◯	◯	◯	◯	◯
*(d)	I feel like I am part of a group who share my goals (Select one option)	◯	◯	◯	◯	◯	◯
*(e)	I feel like I am supported by others in this activity (Select one option)	◯	◯	◯	◯	◯	◯
*(f)	I feel like others want me to be involved with them (Select one option)	◯	◯	◯	◯	◯	◯

The following statements relate to the use of the digital exercise system. Please rate how strongly you agree or disagree with each of the following statements by clicking on the appropriate button. There is no right or wrong answer. It is important to indicate how you feel

Please evaluate each question below

		Strongly Disagree	Disagree	Undecided	Agree	Strongly Agree
*(a)	The system encourages me. (Select one option)	◯	◯	◯	◯	◯
*(b)	The system helps me in keeping track of my progress (Select one option)	◯	◯	◯	◯	◯
*(c)	I consider the other users of the system as my peers (Select one option)	◯	◯	◯	◯	◯
*(d)	The system provides me reminders for reaching my personal goals. (Select one option)	◯	◯	◯	◯	◯
*(e)	Using the system is difficult for me (Select one option)	◯	◯	◯	◯	◯
*(f)	In my opinion, the provided content	◯	◯	◯	◯	◯

	is trustworthy (Select one option)					
*(g)	Overall, I consider the system accurate (Select one option)	◯	◯	◯	◯	◯
*(h)	Using the system does not require a lot of effort from me (Select one option)	◯	◯	◯	◯	◯
*(i)	I do not care about the other users of the system (Select one option)	◯	◯	◯	◯	◯
*(j)	The system provides me with appropriate feedback. (Select one option)	◯	◯	◯	◯	◯
*(k)	In my opinion, the provided content is professional (Select one option)	◯	◯	◯	◯	◯
*(l)	Learning from my peers' actions is beneficial for me (Select one option)	◯	◯	◯	◯	◯
*(m)	The system helps me in reaching my goals gradually (Select one option)	◯	◯	◯	◯	◯
*(n)	In my opinion, the provided content is believable (Select one option)	◯	◯	◯	◯	◯
*(o)	Using the system is straightforward for me (Select one option)	◯	◯	◯	◯	◯
*(p)	My chances of exercise regularly improve by using the system (Select one option)	◯	◯	◯	◯	◯
*(q)	It is easy for me to relate to other users' experiences (Select one option)	◯	◯	◯	◯	◯
*(r)	Overall, I consider the system believable (Select one option)	◯	◯	◯	◯	◯
*(s)	I am not going to use the system from now on (Select one option)	◯	◯	◯	◯	◯
*(t)	The system rewards me. (Select one option)	◯	◯	◯	◯	◯
*(u)	I get support from my peers through the system when I need it (Select one option)	◯	◯	◯	◯	◯
*(v)	In my opinion, using the system has an effect on my exercise behaviour (Select one option)	◯	◯	◯	◯	◯
*(w)	Overall, I consider the system professional (Select one option)	◯	◯	◯	◯	◯

Study Two, Qualitative Survey, Phase 2 Mail out.

* Required Information

Page 1	
* Please enter your 7 digit ID number sent to you by SUUNTO email. (Enter a value between 0 and 9999999)	
____	
Please indicate your gender and date of birth.	
*(a)	Gender (Select one option)

	◯	Male
	◯	Female
*(b)	Date of Birth	
	_ /_ /__ [mm/dd/yyyy]	

* What is your marital status? (Select one option)
◯ Married/domestic partnership
◯ Single

* What is the highest degree or level of school you have completed? If currently enrolled, the highest degree you have received so far. (Select one option)	
◯	Never attended school or only attended kindergarten
◯	Grades 1 through 8(Elementary)
◯	Grades 9 through 11 (Some high school)
◯	Grade 12 or GED (High school graduate)
◯	College 1 year to 3 years (Some college of technical school
◯	College 4 years (College graduate)
◯	Graduate School(Advance Degree)

* **Were you exercising regularly in the 12 months before you purchased your device?** (Select one option)
◯ Yes
◯ No

* **Answer this only if you answered NO to Question 5. Have you ever exercised regularly prior to buying the device?** (Select one option) [Answer this question only if answer to Q#5 is NO]
◯ Yes
◯ No

The following questions concern your general use of the internet. Please think about how you usually use the internet when answering these questions. Select only one answer for each question.						
Please evaluate each question below						
		Never	**Rarely**	**Sometimes**	**Very often**	**Always**
*(a)	I use online emails to communicate with those I do not like to deal with in person (Select one option)	◯	◯	◯	◯	◯
*(b)	I add new contacts to my online accounts (e.g., instant message). (Select one option)	◯	◯	◯	◯	◯
*(c)	I meet new people online. (Select one option)	◯	◯	◯	◯	◯
*(d)	Using the Internet interferes with my social life. (Select one option)	◯	◯	◯	◯	◯
*(e)	The Internet helps me keep in touch with friends or family. (Select one option)	◯	◯	◯	◯	◯

The following statements relate to the use of the Suunto movescount system. Please rate how strongly you agree or disagree with each of the following statements by clicking on the appropriate button. There is no right or wrong answer.It is important to indicate how you feel.						
Please evaluate each question below						
		Strongly Disagree	**Disagree**	**Undecided**	**Agree**	**Strongly Agree**
*(a)	The system encourages me. (Select one option)	◯	◯	◯	◯	◯
*(b)	The system helps me in keeping track of my progress (Select one option)	◯	◯	◯	◯	◯
*(c)	I consider the other users of the system as my peers (Select one option)	◯	◯	◯	◯	◯
*(d)	The system provides me reminders for reaching my personal goals. (Select one option)	◯	◯	◯	◯	◯
*(e)	Using the system is difficult for me (Select one option)	◯	◯	◯	◯	◯
*(f)	In my opinion, the provided content is trustworthy (Select one option)	◯	◯	◯	◯	◯
*(g)	Overall, I consider the system accurate (Select one option)	◯	◯	◯	◯	◯
*(h)	Using the system does not require a lot of effort from me (Select one option)	◯	◯	◯	◯	◯
*(i)	I do not care about the other users of the system (Select one option)	◯	◯	◯	◯	◯
*(j)	The system provides me with appropriate feedback. (Select one option)	◯	◯	◯	◯	◯
*(k)	In my opinion, the provided content is professional (Select one option)	◯	◯	◯	◯	◯
*(l)	Learning from my peers' actions is beneficial for me (Select one option)	◯	◯	◯	◯	◯
*(m)	The system helps me in reaching my goals gradually (Select one option)	◯	◯	◯	◯	◯

*(n)	In my opinion, the provided content is believable (Select one option)					
*(o)	Using the system is straightforward for me (Select one option)					
*(p)	My chances of exercise regularly improve by using the system (Select one option)					
*(q)	It is easy for me to relate to other users' experiences (Select one option)					
*(r)	Overall, I consider the system believable (Select one option)					
*(s)	I am not going to use the system from now on (Select one option)					
*(t)	The system rewards me. (Select one option)					
*(u)	I get support from my peers through the system when I need it (Select one option)					
*(v)	In my opinion, using the system has an effect on my exercise behaviour (Select one option)					
*(w)	Overall, I consider the system professional (Select one option)					
*(x)	In my opinion, the provided content is accurate (Select one option)					
*(y)	The system makes it easier for me to reach my goals (Select one option)					
*(z)	Overall, I consider the system trustworthy (Select one option)					
*(aa)	Through the system, I can share my experiences with my peers (Select one option)					
*(ab)	I am going to continue using the system (Select one option)					

Please indicate how frequently you use the following Suunto digital exercise system functions

Please evaluate each question below

		Never	Occasionally	Regularly	Frequently
*(a)	Wearing the device to record an exercise session (Select one option)	◯	◯	◯	◯
*(b)	Logging into the online system (Select one option)	◯	◯	◯	◯
*(c)	Uploading an exercise move to the online system (Select one option)	◯	◯	◯	◯
*(d)	Adding a SHOUT comment to your own move (Select one option)	◯	◯	◯	◯
*(e)	Adding a SHOUT comment to another person's move (Select one option)	◯	◯	◯	◯
*(f)	Following another user on the online system (Select one option)	◯	◯	◯	◯
*(g)	Giving a THUMB to another user's move on the online system (Select one option)	◯	◯	◯	◯
*(h)	Join a group online (Select one option)	◯	◯	◯	◯
*(i)	Add a SHOUT comment to a GROUP (Select one option)	◯	◯	◯	◯
*(j)	Downloading an app online to use with your device (Select one option)	◯	◯	◯	◯

The following statements represent different feelings people have when they engage in physical activity. Please answer the following question by considering how YOU TYPICALLY feel when participating in physical activity using the scale provided.

Please evaluate each question below

		False	Mostly false	More false than true	More true than false	Mostly true	True
*(a)	I feel like I have developed a close bond with others (Select one option)	◯	◯	◯	◯	◯	◯
*(b)	I feel like I fit in well with others (Select one option)	◯	◯	◯	◯	◯	◯
*(c)	I feel like I am included by others (Select one option)	◯	◯	◯	◯	◯	◯
*(d)	I feel like I am part of a group who share my goals (Select one option)	◯	◯	◯	◯	◯	◯
*(e)	I feel like I am supported by others in this activity (Select one option)	◯	◯	◯	◯	◯	◯
*(f)	I feel like others want me to be involved with them (Select one option)	◯	◯	◯	◯	◯	◯

Appendix C

Variable Descriptions for Study Datasets

C Table 1 *User Demographics Variables*

Variable Name	Description
ModUserID	A unique systems identification number for each registered user of the system.
PostalCountry	The country of origin for the registration of the user in the system.
ProfileCreated	The date that the user's system profile was created and first saved.
BirthDate	The date of birth of the user.
IsMale	Indicates the gender of the user, Male or not Male (therefore designated Female).
LastLoginDate	This is the last date the user logged into the SUUNTO movescount.com system.
FlickrActivatedDate	If the user has a valid Flickr social media account they can activate it on the SUUNTO system and have their MOVE content published to this service.
TwitterActivatedDate	If the user has a valid Twitter social media account they can activate it on the SUUNTO system and have their MOVE content published to this service.
FacebookActivatedDate	If the user has a valid Facebook social media account they can activate it on the SUUNTO system and have their MOVE content published to this service.
YouTubeActivatedDate	If the user has a valid YouTube social media account they can activate it on the SUUNTO system and have their MOVE content published to this service.
DefaultActivity	The primary physical activity done by the user.

C Table 2 *User Anthropometrics Variables*

Variable Name	Description
Weight	User entered weight measured in kilograms.
BMI	This is the Body Mass Index (BMI) of the individual. It has been approximated by the system using a standard algorithm: $BMI = Weight(kg)/Height(m)2$
RestHeartRate	This is the resting heart rate in beats per minute (bpm) of the individual as measured by the vendor's heart rate monitor (HRM).
FitnessIndex	This is a user-entered value recorded by the system to categorise the overall level of physical activity the user typically engages in over the period of a week, defined in Table 15.

C Table 3 Suunto movescount Fitness Index Values

User Reported Value	Meaning
1.0 (Walk for pleasure)	You do not participate regularly in recreational sports or heavy physical activity, perhaps just walking or doing some light exercise.
2.0 (10-60 minutes/week)	You participate regularly in recreational sports or
3.0 (Over 1 hour/week)	do physical work.
4.0 (Under 30 minutes/week)	You participate regularly in sports or other
5.0 (30-60 minutes/week)	physical activity, and you exercise heavily.
6.0 (1-3 hours/week)	
7.0 (Over 3 hours/week)	
7.5 (5-7 hours/week)	You train on a regular basis or participate in
8.0 (7-9 hours/week)	competitive sports.
8.5 (9-11 hours/week)	
9.0 (11-13 hours/week)	
9.5 (13-15 hours/week)	
10.0 (Over 15 hours/week)	

C Table 4 Uploaded Moves Variables

Variable Name	Description
ModMovID	When a user completes an exercise session and uploads it to their movescount account on the system it is recorded as a move and the system provides each move instance with a unique identifier number.
ModUserID	This is the system user identity number of the user who uploaded the move.
ActivityName	This is the name of the physical activity completed by the user the exercise effort for which is uploaded as a move.
StartDate	This is the date of the user move.
HrAvg	This is the average heart rate of the user calculated y the device during the specific move uploaded to the system measured in beats per minute (bpm).
12TrainingEffect	This is a measure derived by Suunto, for which no public algorithmic information is available to the study that combines information provided by the user's heart rate, heart rate variation, and respiratory rate and provides a scale-based level of exertion and effectiveness of training effort as shown in Table 20.
Calories	A unit of energy consumption used to measure the amount of energy consumed by the user while exercising and expressed as Kcals.
Feeling	Feeling is a self-rating of how the user feels about their exercise effort on a 1 (Poor) to 5 (Excellent) scale and is uploaded if the user chooses to do so. Each move uploaded can have a Feeling value ascribed to it.
PublishedtoFacebook	This indicates whether or not the user has published their move data to their Facebook account as a post.

[12] The method seems to use heart rates over the duration of the exercise and calculates relative intensity based on how close exercise heart rate is to its predicted maximal heart rate. This is very similar to the heart rate training zones often used to calculate for an athlete following a maximal exercise test except that maximal heart rate in this instance is assumed. The PTE value that is attained is then used to calculate the recovery time variable and is likely to incorporate variable such as age into its calculation.

C Table 5 *Suunto movescount Training Effect (TE) scale*

TE score	Suunto description
1 minor training effect	Improves recuperation and doesn't advance aerobic endurance.
2 maintain training effect	Maintains aerobic endurance and allows for better cardio-vascular function and more intense training in the future.
3 improving training effect	This improves aerobic condition if performed 2 to 4 times per week. Training at this level does not require special conditions for recovery.
4 highly improving training effect	If repeated 1 to 2 times per week will highly improve aerobic condition. For optimal t requires 2 to 3 recovery workouts (TE 1 to 2) per week.
5 over-reaching training effect	This has a major effect on boosting aerobic condition but requires a sufficient recovery.

C Table 6 *Thumbs file variables*

Variable Name	Description
ModMovID	When a user completes an exercise session and uploads it to their movescount account on the system it is recorded as a move and the system provides each move instance with a unique identifier number.
ModUserID	This is the system user identity number of the user who uploaded the move.
ThumberUserID	This is the system user identity number of the user who is thumbing the move

C Table 7 *General Shouts variables*

Variable Name	Description
ShouterUserID	This is the system user identity number of the user who originated the SHOUT toward another user as part of general use of the system. This SHOUT is not necessarily associated with a specific move of the user who is shouted at.
ShoutedUserID	This is the system user identity number of the user who received a SHOUT from another user as part of general use of the system. This SHOUT is not necessarily associated with a specific move of the user who was shouted at.
DateShouted	This is the date the SHOUT was uploaded and recorded by the system.

C Table 8 *Shouts at Moves variables*

Variable Name	Description
ShouterUserID	This is the system user identity number of the user who originated the SHOUT toward another user as part of general use of the system. This SHOUT is not necessarily associated with a specific move of the user who is shouted at.
ShoutedUserID	This is the system user identity number of the user who received a SHOUT from another user as part of general use of the system. This SHOUT is not necessarily associated with a specific move of the user who was shouted at.
ModMoveID	When a user completes an exercise session and uploads it to their movescount account on the system it is recorded as a move and the system provides each move instance with a unique identifier number. Another user who wishes to make a comment can shout at this move.
DateShouted	This is the date the SHOUT was uploaded and recorded by the system.

C Table 9 *Variables for the Groups Users Belong To*

Variable Name	Description
ModUserID	This is the unique system user identity number of the user.
Joined-Date	This is the date the user joined the Group.
ModGroupID	This is the unique system identified number for each Group created on the system.

C Table 10 *Users Who Create Groups Variables*

Variable Name	Description
ModCreatedBy	This is the unique system user identity number of the user who created the Group. A user can create one or more Groups on the system.
ModGroupID	This is the unique system identified number for each Group created on the system.

Appendix D

Data transformation steps

SQL Data transformation

Suunto provided source data from their SQL Server database as an individual text file per table. Ideally data would have been provided in a single extract that included table creation definitions and data insert statements in the correct order so as to satisfy foreign key constraints (necessary data relationships between tables). Further, export file definitions were provided as a text description for each table. Table creation statements had to be coded from these. Because Suunto sourced the data supplied from their database as output from query extracts and these queries were de-normalised they often contained significant duplicate data. This made the exercise one of determining an appropriate database structure to receive this data and for that to be useful for reliable data analysis. The total data set provided was a subset of the total Suunto database and this subset was selected based on the user status of opted-in for health research usage as the prime selection criterion. As a result, there were instances in the data files of a high percentage of references to data that did not exist inside the subset. This made importing and processing of these files a long process as data rows that had columns that were unresolved references had to be either accepted as benign or removed in order to maintain integrity.

The data file extracts used formats and valid values that would not import into the target mySQL database without calling handcrafted data mapping routines. Reference data (static lookup data like ‘years of education’, ‘occupation’, ‘health level’) was provided as a text description. Reference table definitions had to be created from these and data population scripts added. The data files did not have any representation of a null value, as opposed to an empty value or a blank value. The distinction is important as a null value in a column that is a key into another table can be ignored (if allowed). Any other value must map to a valid value in the foreign table. Significant effort was put into identifying what in the data constituted a null and mapping that data to a mySQL null; this was done in conjunction with the vendor at all times to ensure data integrity. The standard mySQL import processors could not be configured to cater for this in any standard way. Once an appropriate data entity model and matching table definitions were created, it was a separate task to determine the correct order in which the data files could be imported. Obviously data that is then referred to by subsequent data must be made available in the database first. The other option is to import all data without restriction and then attempt to apply data integrity after the fact; this was seemed unacceptable for accurate and valid outcomes from downstream statistical processing. The minimal error/exception reporting in MySQL (and to be fair in most other databases) when attempting this retrospective approach precluded it from use. The *import.sql* file listed in Appendix D is the end product of this problem solving and programmatic process. It was used as the basis for input into the STATA application and downstream statistical analyses used to generate the results for the four studies comprising the thesis.

Functional description of exercise tracking software used in the studies

The Suunto system enables the user to login to the online movescount.com system to upload their exercise sessions recorded by their smart watches (exercise sessions are known by the system as *moves*), manage their account and follow the activities of others including groups they may be members of or have created. During such login events they can alter data including Profile, Body Metrics, Moves Count Settings (privacy settings, measurement units, social media account activations, Health Research opt-in/out). They can also *shout* (comment) on their own or others *moves;* indicate a *thumbs-up* (there is no thumbs down function) for their own or another's *move* or they can *also follow* the activities of another user. Other users who have an interest in the user and or their moves may also follow them. All users of the system have the option to publish their moves to one or more social media accounts including Facebook, Flickr, YouTube and Twitter. A user login to the movescount.com does not mean that a user has uploaded a move, although a user needs to login in order to upload a move. In effect, a user can simply browse the site and online social interactions without engaging in conversation or any other interaction.

MySQL Source Codebase for Suunto Data Transformation

```
-- http://dev.mysql.com/doc/refman/5.5/en/load-data.html
set names utf8;
show character set;
-- SET foreign_key_checks = 0;
select * from suunto.userheaderdata;
delete from suunto.userheaderdata;
-- update userheaderdata set ModUserID = 5812856 where ModUserID = 0;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
\20131028_MCResearchDataUTF8\\UserHeaderData-NoHdr.csv' into table
suunto.userheaderdata
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
(ModUserID,PostalCountry,PublicityLevel,@PublicityLevelChangedDate,Status,
Messages,ProfileCreated,BirthDate,Language,@MetricUnits,
@IsMale,Location,@LastLoginDate,LoginCount,LocalTimeOffsetFromUTC,
@FlickrActivatedDate,@YoutubeActivatedDate,@TwitterActivatedDate,
@FacebookActivatedDate,DefaultActivityID,DefaultActivityName,
Level,@Smoking,@ResearchAllowed,YearsOfEducation,
@ExtraQuestions,Occupation)
set metricunits=IF(@MetricUnits='True',1,0),
ismale=IF(@IsMale='True',1,0),
Smoking=IF(@Smoking='True',1,0),
ResearchAllowed=IF(@ResearchAllowed='True',1,0),
ExtraQuestions=IF(@ExtraQuestions='True',1,0),
PublicityLevelChangedDate=IF(@PublicityLevelChangedDate='',null,@PublicityLev
elChangedDate),
LastLoginDate=IF(@LastLoginDate='',null,@LastLoginDate),
FlickrActivatedDate=IF(@FlickrActivatedDate='',null,@FlickrActivatedDate),
YoutubeActivatedDate=IF(@YoutubeActivatedDate='',null,@YoutubeActivatedDate
),
TwitterActivatedDate=IF(@TwitterActivatedDate='',null,@TwitterActivatedDate),
FacebookActivatedDate=IF(@FacebookActivatedDate='',null,@FacebookActivatedD
ate)
;
select * from suunto.usermovedata;
delete from suunto.usermovedata;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
\20131028_MCResearchDataUTF8\\UserMoveData.csv' into table
suunto.usermovedata
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
```

```
(ModMoveID,
ModUserID,
ActivityID,
ActivityName,
DeviceDisplayName,
StartDate,
@Duration,
@HasMedia,
@HasTime,
@Distance,
@HrAvg,
@TE,
@Calories,
@SpeedAvg,
@Feeling,
@PublishedToTwitter,
@PublishedToFacebook,
DateCreated,
DateModified,
@Weather,
@AscentAltitude,
@DescentAltitude,
@AscentTime,
@DescentTime,
@FlatTime,
@CadenceAvg,
@CadenceMax,
@TemperatureAvg,
@TemperatureMax,
@TemperatureMin,
@HighAltitude,
@LowAltitude,
@SpeedMax,
@HrMin,
@HrPeak,
@SampleInterval,
StartDateOriginal,
@HasSamples,
@HasIBIData,
@HasMarks,
@HasTrack,
@HasTags,
@SamplesConverted,
@MarksCopied,
@MarksCalculated,
@RecoveryTime,
@PowerAvg,
@PowerMax,
@EMGAvg,
```

```
@EMGChannels,
@EMGLeft,
@EMGRight,
@EMGTotal,
@EMGFront,
@EMGBack,
@HeadersConverted,
@PeakEpoc,
@MaxVentilation,
@MaxOxygenConsumption,
@MaxBreathingFrequency,
@TimeInZone1,
@TimeInZone2,
@TimeInZone3,
@TimeInZone4,
@TimeInZone5,
@HrLimitLow,
@HrLimitHigh,
@TimeBelowLimits,
@TimeInsideLimits,
@TimeAboveLimits,
@Type,
@SwolfAvg,
@StrokesPerPoolLengthAvg,
@Intensity)
set Duration=IF(@Duration=",null,replace(@Duration,',','.')),
TE=IF(@TE=",null,replace(@TE,',','.')),
SpeedAvg=IF(@SpeedAvg=",null,replace(@SpeedAvg,',','.')),
AscentAltitude=IF(@AscentAltitude=",null,replace(@AscentAltitude,',','.')),
DescentAltitude=IF(@DescentAltitude=",null,replace(@DescentAltitude,',','.')),
AscentTime=IF(@AscentTime=",null,replace(@AscentTime,',','.')),
DescentTime=IF(@DescentTime=",null,replace(@DescentTime,',','.')),
FlatTime=IF(@FlatTime=",null,replace(@FlatTime,',','.')),
CadenceAvg=IF(@CadenceAvg=",null,replace(@CadenceAvg,',','.')),
CadenceMax=IF(@CadenceMax=",null,replace(@CadenceMax,',','.')),
TemperatureAvg=IF(@TemperatureAvg=",null,replace(@TemperatureAvg,',','.')),
TemperatureMax=IF(@TemperatureMax=",null,replace(@TemperatureMax,',','.')),
TemperatureMin=IF(@TemperatureMin=",null,replace(@TemperatureMin,',','.')),
HighAltitude=IF(@HighAltitude=",null,replace(@HighAltitude,',','.')),
LowAltitude=IF(@LowAltitude=",null,replace(@LowAltitude,',','.')),
SpeedMax=IF(@SpeedMax=",null,replace(@SpeedMax,',','.')),
RecoveryTime=IF(@RecoveryTime=",null,replace(@RecoveryTime,',','.')),
PowerAvg=IF(@PowerAvg=",null,replace(@PowerAvg,',','.')),
PowerMax=IF(@PowerMax=",null,replace(@PowerMax,',','.')),
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EMGRight=IF(@EMGRight=",null,replace(@EMGRight,',','.')),
EMGTotal=IF(@EMGTotal=",null,replace(@EMGTotal,',','.')),
EMGFront=IF(@EMGFront=",null,replace(@EMGFront,',','.')),
EMGBack=IF(@EMGBack=",null,replace(@EMGBack,',','.')),
```

```
PeakEpoc=IF(@PeakEpoc='',null,replace(@PeakEpoc,',','.')),
TimeInZone1=IF(@TimeInZone1='',null,replace(@TimeInZone1,',','.')),
TimeInZone2=IF(@TimeInZone2='',null,replace(@TimeInZone2,',','.')),
TimeInZone3=IF(@TimeInZone3='',null,replace(@TimeInZone3,',','.')),
TimeInZone4=IF(@TimeInZone4='',null,replace(@TimeInZone4,',','.')),
TimeInZone5=IF(@TimeInZone5='',null,replace(@TimeInZone5,',','.')),
SwolfAvg=IF(@SwolfAvg='',null,replace(@SwolfAvg,',','.')),
StrokesPerPoolLengthAvg=IF(@StrokesPerPoolLengthAvg='',null,replace(@Strokes
PerPoolLengthAvg,',
','.')),
HasMedia=IF(@HasMedia='True',1,0),
HasTime=IF(@HasTime='True',1,0),
PublishedToTwitter=IF(@PublishedToTwitter='True',1,0),
PublishedToFacebook=IF(@PublishedToFacebook='True',1,0),
HasSamples=IF(@HasSamples='True',1,0),
HasIBIData=IF(@HasIBIData='True',1,0),
HasMarks=IF(@HasMarks='True',1,0),
HasTrack=IF(@HasTrack='True',1,0),
HasTags=IF(@HasTags='True',1,0),
SamplesConverted=IF(@SamplesConverted='True',1,0),
MarksCopied=IF(@MarksCopied='True',1,0),
MarksCalculated=IF(@MarksCalculated='True',1,0),
HeadersConverted=IF(@HeadersConverted='True',1,0),
Distance=IF(@Distance='',null,@Distance),
HrAvg=IF(@HrAvg='',null,@HrAvg),
Calories=IF(@Calories='',null,@Calories),
Feeling=IF(@Feeling='',null,@Feeling),
Weather=IF(@Weather='',null,@Weather),
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EMGAvg=IF(@EMGAvg='',null,@EMGAvg),
EMGChannels=IF(@EMGChannels='',null,@EMGChannels),
MaxVentilation=IF(@MaxVentilation='',null,@MaxVentilation),
MaxOxygenConsumption=IF(@MaxOxygenConsumption='',null,@MaxOxygenCons
umption),
MaxBreathingFrequency=IF(@MaxBreathingFrequency='',null,@MaxBreathingFreq
uency),
HrLimitLow=IF(@HrLimitLow='',null,@HrLimitLow),
HrLimitHigh=IF(@HrLimitHigh='',null,@HrLimitHigh),
TimeBelowLimits=IF(@TimeBelowLimits='',null,@TimeBelowLimits),
TimeInsideLimits=IF(@TimeInsideLimits='',null,@TimeInsideLimits),
TimeAboveLimits=IF(@TimeAboveLimits='',null,@TimeAboveLimits),
Type=IF(@Type='',null,@Type),
Intensity=IF(@Intensity='',null,@Intensity)
;
select * from suunto.AllGroupsUsersBelongsTo;
delete from suunto.AllGroupsUsersBelongsTo;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
```

```
\20131028_MCResearchDataUTF8\\AllGroupsUsersBelongTo.csv'
into table suunto.AllGroupsUsersBelongsTo
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
(
ModGroupID,
Name,
Description,
Status,
StatusModified,
ImageURL,
AddressID,
ModCreatedBy,
Created,
ModModifiedBy,
Modified,
Location,
Latitude,
Longitude,
TotalNumberOfMembers
);
select * from suunto.UserGroupBelongings;
delete from suunto.UserGroupBelongings;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
\20131028_MCResearchDataUTF8\\UserGroupBelongings.csv'
into table suunto.UserGroupBelongings
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
(
ModUserID,
JoinedDate,
ModGroupID
);
-- above ignoring as dup from basic group data?,
-- Name,
-- Description,
-- Status,
-- StatusModified,
-- ImageURL,
-- AddressID,
-- ModCreatedBy,
-- Created,
-- ModModifiedBy,
-- Modified,
-- Location,
```

```
-- Latitude,
-- Longitude
select * from suunto.UserCreatedGroupData;
delete from suunto.UserCreatedGroupData;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
\20131028_MCResearchDataUTF8\\UserCreatedGroupsData.csv'
into table suunto.UserCreatedGroupData
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
(
ModGroupID,
ModCreatedBy
);
-- Name,
-- Description,
-- Status,
-- StatusModified,
-- ImageURL,
-- AddressID,
-- Created,
-- ModModifiedBy,
-- Modified,
-- Location,
-- Latitude,
-- Longitude,
-- TotalNumberOfMembers
select * from suunto.UsersFollowed;
delete from suunto.UsersFollowed;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
\20131028_MCResearchDataUTF8\\UsersFollowed.csv'
into table suunto.UsersFollowed
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
(
FollowedUserID,
FollowingUserID,
FollowStartDateTime,
@FollowEndDateTime
)
set FollowEndDateTime=IF(@FollowEndDateTime='',null,@FollowEndDateTime);
select * from suunto.UsersFollowing;
delete from suunto.UsersFollowing;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
\20131028_MCResearchDataUTF8\\UsersFollowing.csv'
into table suunto.UsersFollowing
```

```
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
(
FollowingUserID,
FollowedUserID,
FollowStartDateTime,
@FollowEndDateTime
)
set FollowEndDateTime=IF(@FollowEndDateTime='',null,@FollowEndDateTime);
select * from suunto.ShouterUsers;
delete from suunto.ShouterUsers;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
\20131028_MCResearchDataUTF8\\ShouterUsers.csv'
into table suunto.ShouterUsers
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
(
ShouterUserID,
ShoutedUserID,
DateCommented
);
select * from suunto.ShoutsTowardsUser;
delete from suunto.ShoutsTowardsUser;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
\20131028_MCResearchDataUTF8\\ShoutsTowardsUser.csv'
into table suunto.ShoutsTowardsUser
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
(
ShoutedUserID,
ShouterUserID,
DateCommented
);
select * from suunto.UserMoveShouts;
delete from suunto.UserMoveShouts;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
\20131028_MCResearchDataUTF8\\UserMoveShouts.csv'
into table suunto.UserMoveShouts
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
(
```

```
ModMoveID,
ModUserID,
ShouterID,
ShoutDateCommented
);
select * from suunto.UserMoveThumbs;
delete from suunto.UserMoveThumbs;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
\20131028_MCResearchDataUTF8\\UserMoveThumbs.csv'
into table suunto.UserMoveThumbs
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
(
ModMoveID,
ModUserID,
ThumberUserID,
ThumbTimestamp
);
select * from suunto.MovesUserThumbed;
delete from suunto.MovesUserThumbed;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
\20131028_MCResearchDataUTF8\\MoveUsersThumbed.csv'
into table suunto.MovesUserThumbed
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
(
ModUserID,
ThumbedMoveID,
ThumbedUserID,
ThumbTimestamp
);
select * from suunto.UserHistory;
delete from suunto.UserHistory;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
\20131028_MCResearchDataUTF8\\UserHistory.csv'
into table suunto.UserHistory
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
(
ModUserID,
UserHistoryID,
Weight,
Height,
```

```
BMI,
RestHr,
MaxHr,
FitnessIndex,
HrZone1,
HrZone2,
HrZone3,
HrZone4,
Timestamp
);
select * from suunto.TempEvents;
delete from suunto.TempEvents;
select * from suunto.Event;
delete from suunto.Event;
select * from suunto.UserEvent;
delete from suunto.UserEvent;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
\20131028_MCResearchDataUTF8\\Events-Clean.csv'
into table suunto.TempEvents
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
(
ModUserID,
ModEventID,
EventName,
StartDateTime,
JoinedDate
);
insert into event (ModEventID,EventName, StartDateTime)
select distinct ModEventID, EventName, StartDateTime from TempEvents;
insert into UserEvent (ModUserID,ModEventID,JoinedDate)
select distinct ModUserID,ModEventID,JoinedDate from TempEvents;
select * from suunto.UserGroupBelongingsShouts;
delete from suunto.UserGroupBelongingsShouts;
load data local infile 'C:\\daryl\\data\\20131028_FullDataUCS2andUFT8\\
\20131028_MCResearchDataUTF8\\UserGroupBelongingsShouts.csv'
into table suunto.UserGroupBelongingsShouts
character set utf8
fields terminated by ','
enclosed by '"'
lines terminated by '\r\n'
(
ModGroupID,
Name,
ModShoutID,
@ModParentShoutID,
ModShouterID,
```

```
DateCommented
)
set ModParentShoutID = IF(@ModParentShoutID='',null,ModParentShoutID);
-- REMOVE HEADER BOGUS rows
delete from usermovedata where ModMoveID = 0;
delete from UserCreatedGroupData where ModGroupID = 0 and ModCreatedBy =0;
delete from UsersFollowed where followinguserId =0 and followeduserid=0;
delete from UsersFollowing where followinguserId =0 and followeduserid=0;
delete from ShouterUsers where shouteruserID =0 and shouteduserID =0;
delete from ShoutsTowardsUser where shouteruserID =0 and shouteduserID =0;
delete from UserMoveShouts where modmoveID =0;
delete from UserMoveThumbs where modmoveID =0;
delete from movesuserthumbed where moduserid =0;
delete from UserHistory where moduserid =0;
delete from UserEvent where moduserid =0;
-- other clean up
update usermovedata set feeling = null where feeling = 0;
```

Appendix E

Study One Tables

E Table 1 Frequency Table

	N	%
Gender		
Male	2,127	10.64
Female	17,873	89.36
Top 5 Default Activities		
Not specified	6.902	34.51
Running	5,661	28.3
Cycling	1,017	5.08
Mountain biking	754	3.77
Indoor cycling	363	1.81
Social Media Account Activation		
FlickR	115	0.64
Facebook	2,204	11.02
YouTube	519	2.6
Twitter	528	2.64

E Table 2 Login Count and Age

	Mean	sd	Min.	Max.	Perc.25	Perc.50	Perc.75
Age	39.03	9.97	0	82	32	39	45
Login Count	7.37	18.04	0	476	0	0	7

E Table 3 Stepwise Regression of Standardized Login Count on Demographics

	Coefficient	Robust Std. Err.	t	P>|t|	95% LCL	95% UCL
Intercept	-0.231	0.017	-13.690	0.000	-0.265	-0.198
Age standardized	0.020	0.007	2.810	0.005	0.006	0.034
Male	0.135	0.017	7.850	0.000	0.101	0.168

	Coefficient	Robust Std. Err.	t	P>|t|	95% LCL	95% UCL
Flickr account	1.507	0.329	4.580	0.000	0.862	2.152
YouTube channel	0.211	0.083	2.550	0.011	0.049	0.373
Countries						
Angola	1.514	0.010	154.030	0.000	1.495	1.533
Cyprus	0.412	0.246	1.680	0.094	-0.070	0.894
Belgium	0.374	0.109	3.430	0.001	0.160	0.588
France	0.264	0.040	6.630	0.000	0.186	0.342
Austria	0.262	0.058	4.510	0.000	0.148	0.376
Bahamas	0.261	0.133	1.970	0.049	0.001	0.521
Spain	0.203	0.045	4.550	0.000	0.116	0.291
Sweden	0.131	0.048	2.730	0.006	0.037	0.225
Germany	0.129	0.045	2.870	0.004	0.041	0.217
Maldives	0.105	0.052	2.040	0.042	0.004	0.206
Great Britain & N. Ireland	0.094	0.038	2.500	0.012	0.020	0.168
South Africa	0.094	0.048	1.960	0.050	0.000	0.188
Switzerland	0.075	0.041	1.830	0.067	-0.005	0.156
Italy	0.074	0.034	2.180	0.029	0.007	0.140
Australia	0.057	0.029	1.970	0.049	0.000	0.114
Kuwait	-0.141	0.017	-8.390	0.000	-0.174	-0.108
Croatia	-0.182	0.050	-3.620	0.000	-0.280	-0.083
Belarus	-0.191	0.098	-1.950	0.051	-0.382	0.001
Panama	-0.193	0.071	-2.700	0.007	-0.333	-0.053
Moldova	-0.233	0.046	-5.110	0.000	-0.322	-0.143
Nepal	-0.234	0.043	-5.420	0.000	-0.319	-0.149
Tanzania	-0.243	0.060	-4.080	0.000	-0.359	-0.126
Ecuador	-0.244	0.076	-3.230	0.001	-0.392	-0.096
Bahrain	-0.303	0.011	-27.390	0.000	-0.325	-0.281
Madagascar	-0.305	0.010	-30.450	0.000	-0.325	-0.285
Republic of Macedonia	-0.306	0.014	-22.230	0.000	-0.333	-0.279
Jordan	-0.309	0.047	-6.610	0.000	-0.401	-0.218
Guadeloupe	-0.312	0.012	-26.710	0.000	-0.335	-0.289
Papua New Guinea	-0.314	0.010	-31.280	0.000	-0.334	-0.295
Bolivia	-0.315	0.012	-25.600	0.000	-0.340	-0.291
Algeria	-0.318	0.095	-3.340	0.001	-0.504	-0.131
French Guiana	-0.326	0.015	-21.820	0.000	-0.355	-0.296
Saudi Arabia	-0.551	0.232	-2.380	0.017	-1.006	-0.097

Activities						
Ski Touring	0.199	0.082	2.440	0.015	0.039	0.360
Cross Country Skiing	0.193	0.056	3.440	0.001	0.083	0.303

	Coefficient	Robust Std. Err.	t	P>|t|	95% LCL	95% UCL
Trail Running	0.133	0.039	3.390	0.001	0.056	0.210
Run	0.029	0.016	1.770	0.077	-0.003	0.061
Trekking	-0.087	0.037	-2.340	0.019	-0.160	-0.014
Mountaineering	-0.118	0.058	-2.030	0.043	-0.232	-0.004
Climbing	-0.157	0.083	-1.900	0.058	-0.319	0.005
Volleyball	-0.174	0.085	-2.040	0.041	-0.341	-0.007
Dancing	-0.186	0.079	-2.340	0.019	-0.341	-0.030
Yoga Pilates	-0.191	0.084	-2.280	0.023	-0.356	-0.027
Table Tennis	-0.194	0.063	-3.090	0.002	-0.316	-0.071
Combat Sport	-0.219	0.060	-3.630	0.000	-0.337	-0.100
Telemark Skiing	-0.219	0.126	-1.750	0.081	-0.465	0.027
Ice Skating	-0.221	0.074	-3.000	0.003	-0.365	-0.076
Golf	-0.234	0.044	-5.380	0.000	-0.320	-0.149
Ice Hockey	-0.242	0.045	-5.420	0.000	-0.329	-0.154
Orienteering	-0.260	0.061	-4.270	0.000	-0.379	-0.141
Kettlebell	-0.296	0.072	-4.110	0.000	-0.437	-0.155
Windsurfing/Surfing	-0.301	0.031	-9.750	0.000	-0.362	-0.241
Racquet Ball	-0.314	0.137	-2.290	0.022	-0.583	-0.045
Handball	-0.314	0.045	-6.950	0.000	-0.403	-0.226
Bowling	-0.325	0.011	-29.450	0.000	-0.347	-0.304
Treadmill	-0.334	0.016	-21.140	0.000	-0.365	-0.303
Nordic Walking	-0.348	0.047	-7.330	0.000	-0.441	-0.255
Football	-0.372	0.037	-10.080	0.000	-0.445	-0.300
Open Water Skiing	-0.404	0.052	-7.830	0.000	-0.505	-0.303
Paragliding	-0.459	0.062	-7.350	0.000	-0.582	-0.337

E Table 4 Descriptive Statistics for User Anthropometrics Data

Variable	Count	Mean	sd.	Min	Max	P25	P50	P75
Age	4364	39.65	9.91	1	77	33	40	46
WghtMx	4365	81.25	16.32	42	200	72	80	89
BMIMax	4365	25.58	4.69	16	29	23	25	27
RstHRMx	4365	60.72	7.99	33	100	60	60	60
FitIndex	4365	6.06	1.47	1	10	5	6	7
WtMin	4365	76.52	14.40	31	163	65	75	85
BMIMin	4365	24.19	3.60	12	48	22	23	26
RstHRMn	4365	57.97	7.48	30	100	55	60	60
FitIndMin	4365	5.35	1.52	1	10	5	5	6
WtMean	4365	79.24	14.03	42	167.25	70	78	86.75
BMIMean	4365	24.88	3.73	16	51	22.5	24	26.67
RstHRMn	4365	59.25	7.39	33	100	57.33	60	60

FitInMean	4365	5.74	1.41	1	10	5	5.67	6.75
WtMed	4365	79.50	14.23	42	189	70	78	87.5
BMIMed	4365	24.88	3.77	16	58	22.5	24	27
RstHRMd	4365	59.22	7.73	30	100	58	60	60
FitIndMd	4365	5.76	1.46	1	10	5	6	7
BMIMean	4365	24.88	3.73	16	51	22.5	24	26.67

E Table 5 Correlations of Anthropometric Measures

	Age	Wt Max	BMI Max	Rest HR Max	Fit Index Max	Wt Min	BMI Min	Rest HR Min	Fit Index Min	Wt Mean	BMI Mean	Rest HR Mean	Fit Index Mean	Wt Medn	BMI Medn	Rest HR Medn	Fit Index Medn
Age	1.000																
Wt Max	0.110*																
BMI Max	0.115*	0.868*	1.000														
Rest HR Max	-0.006	0.127*	0.182*														
Fit Index Max	-0.094*	-0.132*	-0.166*	-0.233*													
Wt Min	0.114*	0.734*	0.568*	0.060*	-0.173*												
BMI Min	0.145*	0.669*	0.709*	0.138*	-0.252*	0.844*	1.000										
Rest HR Min	0.005	0.112*	0.161*	0.730*	-0.358*	0.145*	0.215*	1.000									
Fit Index Min	-0.068*	-0.180*	-0.229*	-0.298*	0.705*	-0.085*	-0.185*	-0.262*	1.000								
Wt Mean	0.123*	0.918*	0.753*	0.116*	-0.170*	0.903*	0.805*	0.136*	-0.170*	1.000*							
BMI Mean	0.142*	0.806*	0.896*	0.186*	-0.238*	0.745*	0.915*	0.208*	-0.247*	0.854*	1.000						
Rest HR Mean	0.001	0.131*	0.186*	0.908*	-0.321*	0.121*	0.197*	0.924*	-0.294*	0.141*	0.216*	1.000					
Fit Index Mean	-0.088*	-0.170*	-0.216*	-0.283*	0.923*	-0.151*	-0.243*	-0.345*	0.892*	-0.187*	-0.267*	-0.338*	1.000				
Wt Medn	0.122*	0.884*	0.720*	0.121*	-0.172*	0.868*	0.783*	0.134*	-0.184*	0.987*	0.844*	0.142*	-0.196*	1.000			
BMI Medn	0.142*	0.764*	0.844*	0.189*	-0.243*	0.725*	0.898*	0.210*	-0.256*	0.839*	0.985*	0.218*	-0.275*	0.851*	1.000		
Rest HR Medn	0.000	0.130*	0.182*	0.873*	-0.308*	0.128*	0.200*	0.890*	-0.280*	0.143*	0.214*	0.984*	-0.325*	0.143*	0.216*	1.000	
Fit Index	-0.082*	-0.166*	-0.211*	-0.274*	0.894*	-0.151*	-0.236*	-0.341*	0.850*	-0.183*	-0.259*	-0.333*	0.984*	-0.190*	0.267*	0.321*	1.000

Medn

*Note: *p < 0.001, Max N = 43*

E Table 6 Regression of Login Count on Age, Gender and Anthropometric Measures

Login Count	Coefficient	Std error	t	P>|t|	95% LCL	95% UCL
IsMale	6.084857	1.228206	4.95	0.000	3.676949	8.492766
Age	0.1352202	0.408234	3.31	0.001	0.0551855	0.2152549
FitIdxMed	-4.5488	2.120524	-2.10	0.036	-8.611894	-0.2972817
FitIdxMin	-5.88639	0.834576	-6.70	0.000	-7.224833	-0.3952445
FitIdxMn	12.16403	2.545727	4.78	0.000	7.173109	17.15495
RstHRMax	0.574927	0.1270494	4.53	0.000	0.3258455	0.8240085
RstHRMin	-0.9023547	0.1237337	-7.29	0.000	-1.44936	-0.6597736
WtMean	0.1521072	0.053802	2.85	0.005	0.0466279	0.2575865
BMIMean	-0.9563124	0.1814244	-5.27	0.000	-1.311997	-0.6006284
Constant	21.03531	5.303101	3.97	0.000	10.63583	31.43209

E Table 7 Regression of Login Count on Age, Gender and Means of Anthropometric Measures

Login Count	Coefficient	Standard error	t	P>|t|
IsMale	5.837327	1.259488	4.63	0.000
Age	0.1202018	0.0417374	2.88	0.004
WtMean	0.1408977	0.0551786	2.55	0.011
BMIMean	-0.9013818	0.1844832	-4.89	0.000
RstHRmen	-0.2739982	0.0654974	-4.18	0.000
FitIdxMen	2.47034	0.3037956	8.13	0.000
Constant	20.32923	5.374343	3.78	0.000

E Table 8 Regression of Login Count on Number of Followers for Various Samples with t statistics in parentheses

	Full sample	Through 99th percentile (11 or fewer followers)	Through 95th percentile (4 or fewer followers)

Intercept	4.944*	5.356	7.802*
	(2.029)	(1.668)	(2.085)
Number of people following	11.436***	11.086***	9.296**
	(6.741)	(4.588)	(3.052)
N	874	872	851
R^2	0.143	0.072	0.02
p > F	<0.0001	<0.0001	0.002

*Note:*t statistics in parentheses
*: Significant at 0.05 level of significance
**: Significant at 0.01 level of significance
***: Significant at <0.001 level of significance

E Table 9 Regression of Number of Moves on Number of People Following a User for Various Samples with t statistics in parentheses

	Full sample	Through 99th percentile (11 or fewer followers)	Through 95th percentile (4 or fewer followers)
Intercept	19.738***	19.248***	16.027***
	14.843	12.998	6.281
Number of people following	2.364**	2.730**	5.468**
	3.462	3.168	2.703
N	471	470	455
R^2	0.021	0.020	0.024
p > F	0.001	0.002	0.007

Note: t statistics in parentheses
*: Significant at 0.05 level of significance
**: Significant at 0.01 level of significance
***: Significant at <0.001 level of significance

E Table 10 Regression of Login Count on Number of Users a User Follows for Various Samples, t statistics in parentheses

	Coefficient	SE	t	P>|t|	95% LCL	95% UCL
Number of people followed	0.938	0.065	14.52	0.000	0.811	1.065
Constant	13.819	0.637	21.69	0.000	12.570	15.068

E Table 11 Regression of Number of Moves on Number of People a User Follows for Various Samples, t Statistics in Parentheses

	Full sample	99th Percentile (Following ≤ 27)	95th Percentile (Following ≤ 10)	90th Percentile (Following ≤ 7)
Intercept	18.774***	16.101***	16.072***	15.853***
	(32.442)	(22.837)	(20.904)	(19.232)
Number of people following	0.220**	1.137***	1.120***	1.242***
	(2.782)	(5.624)	(4.276)	(3.816)
N	1,309	1,297	1,244	1,198
R^2	0.018	0.042	0.015	0.011
p>F	0.005	<0.001	<0.001	<0.001

*: Significant at less than 0.05 level of significance
**: Significant at less than 0.01 level of significance
***: Significant at less than 0.001 level of significance

E Table 12 Descriptive Statistics for Training Effect (TE), Feeling, and Calories

Statistic	TE	Feelings	Calories
N	78,631	16,854	92,031
Mean	3.040044	3.573158	606.5559
Standard deviation	1.131802	.9529144	470.0742
Minimum	0	1	0
Maximum	5	5	14046
P25	2.2	3	307
P50	3.1	4	526
P75	3.8	4	794

E Table 13 Correlations between TE, Calories, Average Heart Rate (HrAvg), LoginCount by Activity, and Number of Moves

	TE	Calories	HrAvg	Login count by activity
TE	1.000			
Calories	0.506***	1.000		
HrAvg	0.807***	0.366***	1.000	
Login Count by Activity	0.127***	0.093***	0.137***	1.000
Number of Moves	0.055***	0.009	0.085***	0.440***
TE	1.000	1.000	1.000	1.000

Note: *p < 0.05, **p < 0.01, ***p < 0.0001. *N* ranges from 7,207 to 10,299

E Table 14 A Stepwise Regression of Number of Moves on TE,Calories and HrAvg variables

	Coefficient	Std.Error	t	P>|t|	95%LCL	95%UCL
TE	-3.979	0.637	-6.25	0.000	-5.227	-2.730
HRavg	0.175	0.023	7.46	0.000	0.129	0.221
Calories	0.006	0.001	5.35	0.000	0.004	0.008
Constant	5.577	2.159	2.58	0.010	1.344	9.810

E Table 15 A Stepwise Regression of the Number of Moves on Exercise Intensity-Outcomes and Publish to Twitter

	Coefficient	Robust Std. Err	t	P>|t|	95% LCL	95% UCL
Intercept	20.257	1.365	14.836	0.000	17.580	22.934
TE	-4.619	0.399	-11.590	0.000	-5.400	-3.838
HrAvg	0.080	0.015	5.306	0.000	0.051	0.110
Pub2Twitter	5.130	1.353	3.791	0.000	2.477	7.782

E Table 16 Stepwise regression of Login Count on Exercise Intensity-Outcomes and Publish to Twitter

	Coefficient	Std.Error	t	P>|t|	95%LCL	95%UCL
TE	-3.998	0.551	-7.26	0.000	-5.078	2.918
HrAvg	0.174	0.019	9.25	0.000	0 .137	0.210
Calories	0.006	0.001	5.95	0.000	0 .004	0.008
Pub2Twit	13.244	2.857	4.64	0.000	7.644	18.844
Constant	5.600	1.582	3.54	0.000	2.499	8.700

E Table 17 Descriptive Statistics for Thumbs Received and Sent

	Number of users	Mean	Std deviation	1st quartile	Median	3rd quartile	Min.	Max.
Number of Thumbs Received	2848	2.535	6.805	1	1	2	1	274
Number of Self-Sent Thumbs	2848	1.713	5.342	1	1	2	0	249
Number of Thumbs Sent	3,034	2.379367	7.018	1	1	2	1	250
Proportion that are Self-Sent	3,034	1.608	5.192	0	1	2	0	249

E Table 18 Descriptive statistics for General Shouts Made and Received

	N	Mean	Std.dev.	First quartile	Median	Third quartile	Min.	Max.
Shouts Made	882	4.549	35.422	1	1	3	1	832
Shouts Receive	2,095	1.915	4.066	1	1	2	1	135

E Table 19 A Stepwise Regression of Number of General Shouts Made on Login Count, Anthropometric Measures and Age.

	Coefficient	Std Error	t	P>|t|	95% LCL	95% UCL
Login Count	0.282	0.055	5.12	0.000	0.174	0.391
Constant	-7.315	4.112	-1.78	0.076	-15.412	0.781

E Table 20 A Stepwise Regression of Number of General Shouts Received on Login Count, Anthropometric Measures and Age.

	Coefficient	Std Error	t	P>|t|	95% LCL	95% UCL
Login Count	0.076	0.016	4.89	0.000	0.045	0.107
Constant	-0.670	1.288999	-0.520	0.604	-3.219	1.880

E Table 21 Descriptive Statistics for the Number of Users Receiving Shouts at Moves and Number of Moves Receiving Shouts

	N	Mean	Std. dev.	First quartile	Median	Third quartile	Min.

Users Receiving Shouts	1,467	3.506	7.524	1	1	3	1
Moves Receiving Shouts	3,913	1.314	0.942	1	1	1	1
Moves by Users Receiving Shouts	1,467	2.667	4.904	1	1	2	1

E Table 22 A Stepwise Regression of the Number of Moves Receiving Shouts on Anthropometric Measures

	Coefficient	Std error	t	P>|t|	95% LCL	95% UCL
No. Moves	0.032	0.010	3.14	0.002	0.012	0.052
MinFitIndx	0.483	0.209	2.31	0.022	0.071	0.895
BMIMedn	-0.228	0.084	-2.71	0.007	-0.393	-0.063
MedFitInd	-0.703	0.214	-3.28	0.001	-1.124	-0.0282
Constant	9.277	2.543	3.65	0.000	4.276	14.277

E Table 23 Correlations between the Number of Groups Joined, Login Count, Number of Moves and Anthropometrics Measures

	No. Groups Joined	No. Moves	Login Count	Age	BMI Mean	Weight Mean	RestHR Mean	FitIndx Mean
No. Groups Joined	1.000							
No. Moves	0.164^{+}	1.000						
Login Count	0.316^{+}	0.335^{+}	1.000					
Age	-0.074*	0.043*	0.028	1.000				
BMI Mean	-0.028	-0.074^{+}	-0.098^{+}	0.129^{+}	1.000			
Weight Mean	-0.047	-0.067^{+}	-0.051**	0.108^{+}	0.855^{+}	1.000		
Rest HR Mean	-0.069	-0.138^{+}	-0.124^{+}	0.009	0.244^{+}	0.175^{+}	1.000	
Fitness Index Mean	0.112**	0.240^{+}	0.155^{+}	-0.087^{+}	-0.265^{+}	-0.192^{+}	-0.3534^{+}	1.000

Note: $*p < 0.05$, $**p < 0.01$, $^{+}p < 0.001$.

N = 796 in "No. Groups Joined" column, and N = 3488 in all other columns.

E Table 24 A Regression of the Number of Groups Joined on Anthropometric Measures, Gender and Login Count

	Coefficient	Std error	t	P>|t]	95% LCL	95% UCL
Fitness Index Mean	0.123	0.050	2.48	0.013	0.0255	0.220
IsMale?	0.544	0.204	2.67	0.008	0.144	0.944
LoginCount	0.016	0.003	4.62	0.000	0.009	0.022
Age	-0.022	0.009	-2.55	0.011	-0.040	-0.005
BMI Mean	0.126	0.039	3.22	0.001	0.049	0.203
Weight Mean	-0.030	0.009	-3.33	0.001	-0.048	-0.012
Constant	0.636	0.859	0.74	0.459	-1.049	2.322
Fitness Index Mean	0.123	0.050	2.48	0.013	0.0255	0.220

E Table 25 Descriptive Analysis of Shouts, Users Who Created Groups and Group Members

	N	Mean	Standard deviation	First quartile	Median	Third quartile	Minimum
Users Who Created Groups	48	5.729	9.856	1	2	6.5	1
Group Members	186	2.892	5.86	1	1	3	1

E Table 26 Correlations of the Number of Shouts Within the Group, Login Count, Age and Number of Moves

	Number of Shouts Within Group	Login Count	Age	No. Moves
Number of Shouts Within Group	1.000			
LoginCount	0.553*			
Age	-0.025	0.006		
Number of sessions	0.240	0.317	-0.058	1.000

*Note: *p < 0.001, N = 3*

E Table 27 A Negative Binomial Panel Analysis for the Persistence of Moves Over Time

	Coefficient	SE	Z	P value	95% LCL	95% UCL
No.months since 1st Move	-0.070	0.002	-38.506	<0.001	-0.074	-0.067
HasTwitter	-0.050	0.067	-0.753	0.452	-0.182	0.081
HasFlickr	0.290	0.096	3.008	0.003	0.101	0.478
HasYouTb	0.013	0.061	0.214	0.831	-0.107	0.133
No. Months from start system_	0.166	0.009	17.502	<0.001	0.147	0.184
Age	-0.0003	0.001	-0.356	0.722	-0.002	0.001
Constant	-1.706	0.129	-13.175	<0.001	-1.960	-1.452

E Table 28 Quartiles of Age, Mean Fitness Index and Maximum Weight

	Age, years	Mean Fitness Index	Maximum Weight, kg
First Quartile	31	4.95	73
Median	38	5	82
Third Quartile	45	6.5	91

Appendix F

Invariance Tests for Study Two

The STATA script and dataset for generating this test output has been provided to the University of Tasmania in electronic form.

To run the supplied STATA .do files with its accompanying datset is done from STAT using the DO button.

Files supplied: invaraiance.do and sem data.dta

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Appendix G
Study Two Invitation to Participate Email

Dear <user name>,

SUUNTO Oy and the University of Tasmania invite you to participate in a research study called " Towards an Understanding of Behaviour in an Online Exercise Community". This invitation results from your agreement with SUUNTO Oy to voluntarily participate in health research activities that arise from your purchase and use of SUUNTO Oy products and services. The purpose of this study is to better understand how and why people use the Suunto online exercise system, *movescount.com*.

Your participation requires you to complete an online survey that should take on average about 20 minutes to complete. It is available in English and you can access it here <link>, a secure online survey system. Please note that the researchers have no access to your personal details and your responses are completely anonymous. You have until 12 midnights, July 31st, 2014 to complete this survey if you would like to participate.

If you have any questions concerning the survey please write to the researcher, Daryl Foy of the University of Tasmania at daryl.foy@utas.edu.au.

Thank you for your interest. We hope you can join us in helping better understand how we can help the *movescount.com* system to assist your exercise behaviour.

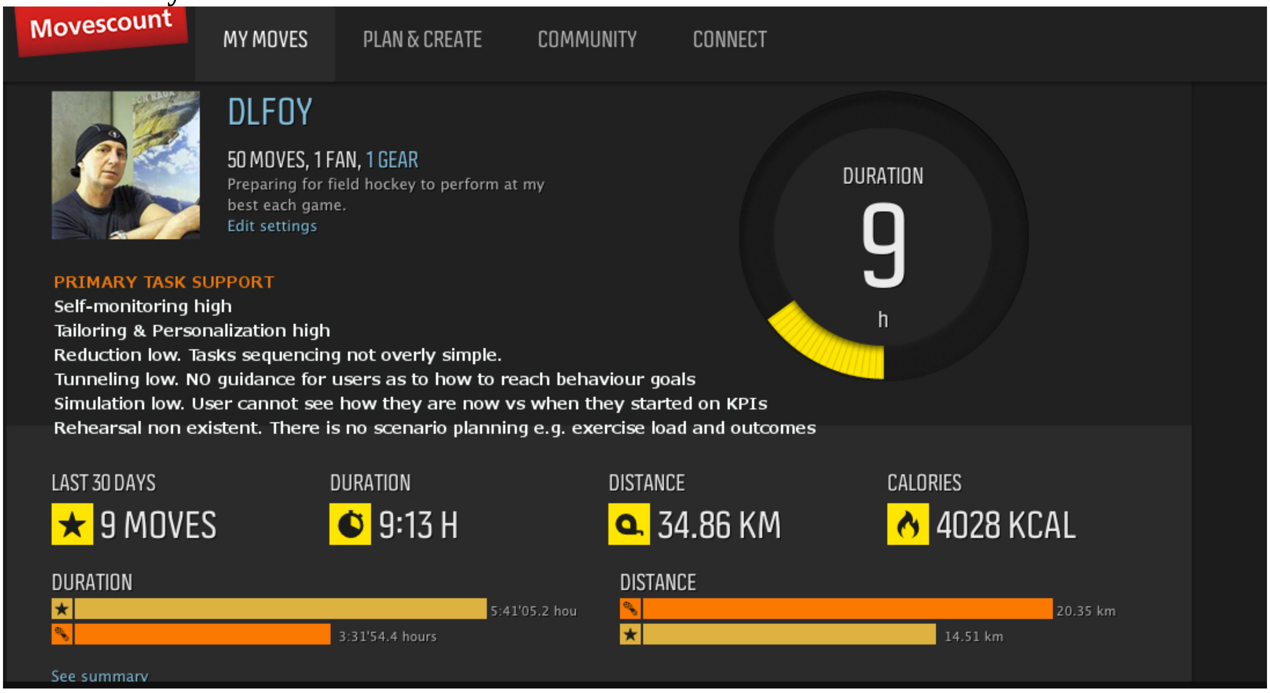
Sincerely yours,

Janne Kallio
Head of Digital Marketing
Suunto Oy

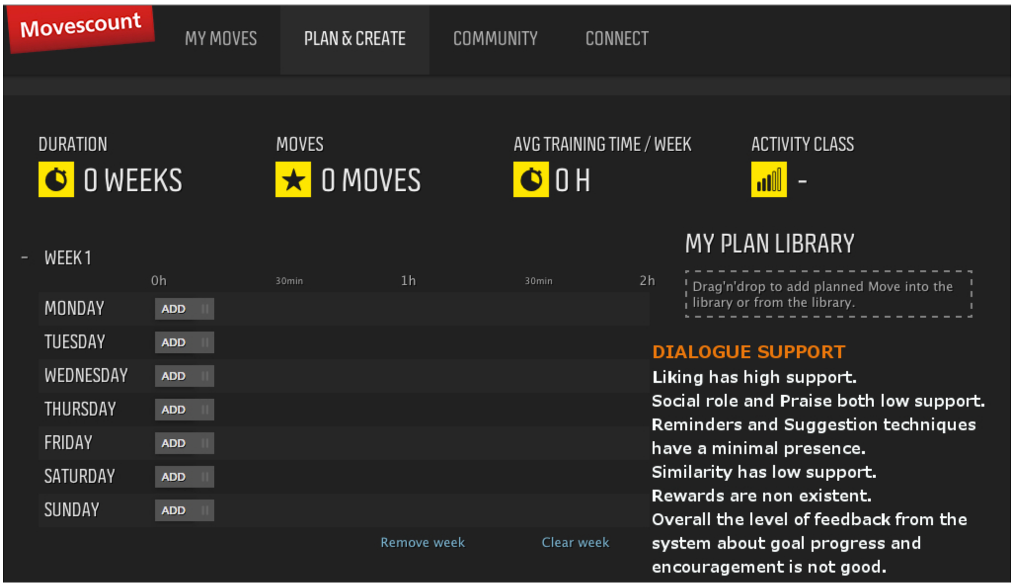
Associate Professor Stuart Smith
University of Tasmania
School of Health Sciences
Director, Healthy Eating, Active Living Technology (HEALTHY) Research Centre

Appendix H

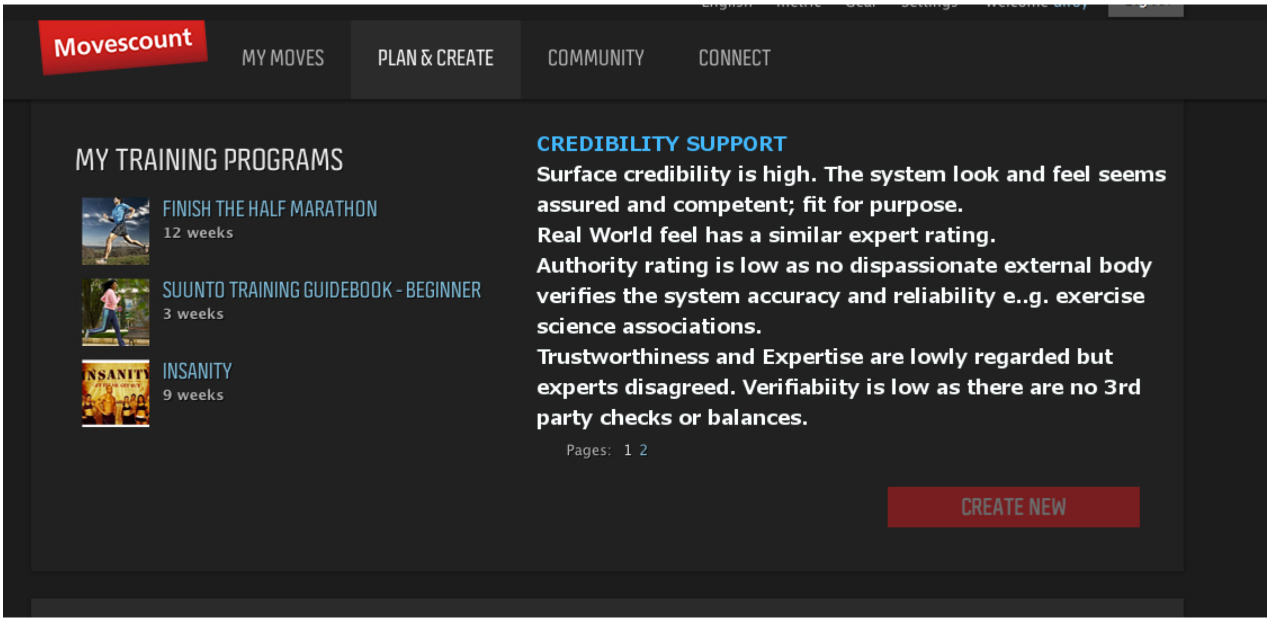
Mapping the movescount.com system to the PSD constructs used the Expert Panel Survey



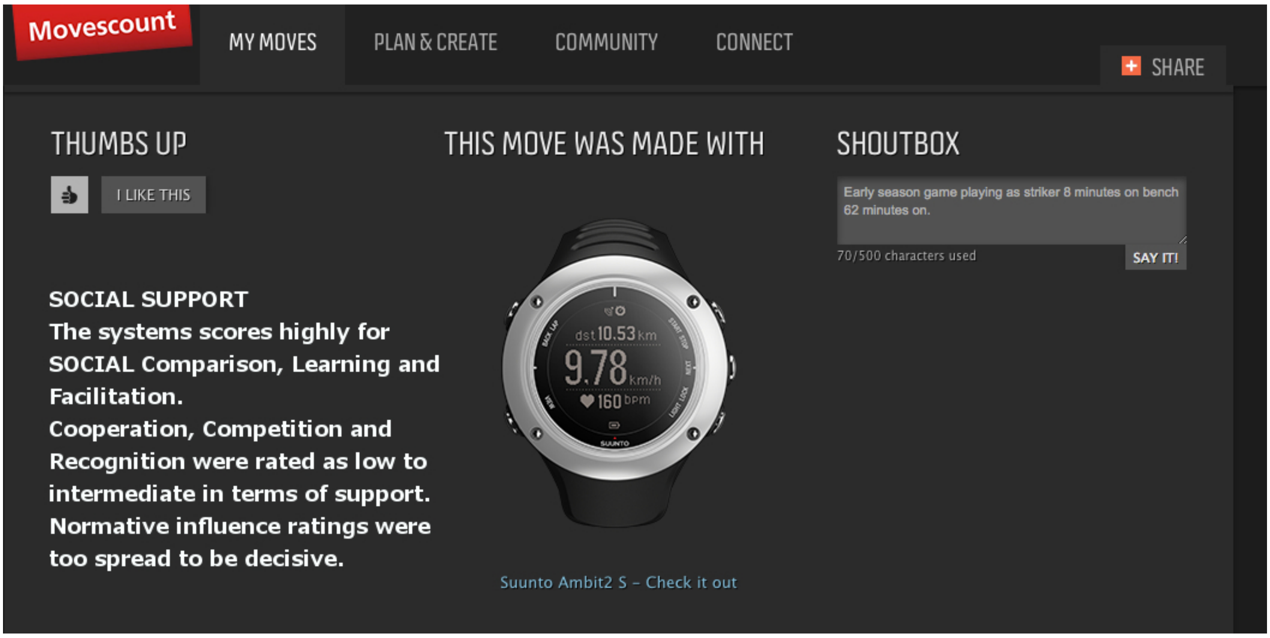
Overview Figure 12. PSD Persuasive Design Element Primary Task Support Expert Rating Summary for movescount.com.



Overview Figure H13. PSD Persuasive Design Element Dialogue Support Expert Rating Summary for movescount.com.



Overview Figure H14. PSD Persuasive Design Element Credibility Support Expert Rating Summary for movescount.com.



Overview Figure H15. PSD Persuasive Design Element Social Support Expert Rating Summary for movescount.com

Overview Figure H16. PSD Movescount Self-Regulation Example Feedback from exercise performance

Appendix I

Structural Equation Model Study Two RQ 15

Principles and Considerations

Structural equation models in the social sciences generally consist of two components: a measurement model and a model of the relationships among the constructs that underpin the measurement model known as the structural model. In this measurement model, the factors that represent latent constructs that were described by the analyses of the population sample under study are assumed to be the causes of the responses from the users to the items on the survey questionnaire. In the structural model, a set of relationships among the constructs is posited which may also involve other observable variables. The advantages of structural equation modelling versus single equation ordinary least squares regression stem from the much richer set of relationships among variables that can be explored. For *example, among the present constructs, online sociability may not be directly related to intention to continue using the movescount.com exercise system, but may still be indirectly related because it affects the value a user attaches to a well-functioning online social support system*. As another example of possible relationships among variables, the values of variables may be jointly determined. For example, it may be that the higher levels of credibility are associated with more favourable views of the exercise system, which in turn enhance the system's credibility, so that credibility can to some extent, be bootstrapped from well-regarded performance features.

A structural equation model may be represented as a set of simultaneous linear equations or through a path diagram. Path diagrams have been used here because they more clearly represent the relationships among variables. In a path diagram, variables whose names are enclosed in circles are latent (i.e., unobserved) variables whereas variables enclosed in rectangles are observed. Directed arrows connect variables in a path diagram. A variable that receives a directed arrow is referred to as an endogenous or system-determined variable because its value is determined by the system of equations of the structural equation model. Any variable that does not receive an arrow but instead only has arrows emanating from it is referred to as an exogenous variable because its value is determined outside the system. Observe that an endogenous variable can be a function of another endogenous variable as well as being a function of exogenous variables.

Whether a variable is regarded as an exogenous variable or an endogenous variable in a model is to some extent determined by the purpose of the model at hand. In this study, among various endogenous variables, the primary focus is on the users intent to continue to use the exercise system. A fairly stringent criterion is used such that the only candidates to be considered as *exogenous variables are variables whose values were determined prior to the time of the survey*. From the survey itself, these include the *demographic variables* as well as the questions regarding *previous exercise behavior*. Any of the variables from the exercise sessions (moves) data are also candidate exogenous variables (e.g., Number of Moves, Login Count). Of course, under this treatment, the usage items on the survey are endogenous variables rather than exogenous variables because usage is currently determined and is a function of the other endogenous variables in the system.

The last item that warrants explanation is model identification. A statistical model is identified if the parameters that are being estimated by the model can be shown to uniquely define a solution for the model. For the structural equation models that are estimated here, the model can be represented by a system of linear equations.

Therefore model identification requires that there is a unique set of parameters that solves this set of equations.

Based on the literature, (Bagozzi & Yi, 1988: Bollen, 1989: Bollen & Long, 1993; Bollen, 2005), when abstracting from the measurement model, linear structural equation systems with observable variables require that *two conditions be satisfied for the model to be identified: an order condition and a rank condition.* The order condition may be stated as the number of excluded exogenous variables from each equation must be at least as large as the number of included endogenous variables in the equation and this condition amounts to the requirement that there be as many equations as there are unknowns. The order condition is a sufficient condition for the system to have at least one solution. To understand the rank condition, define the reduced form of the structural model as a re-expression of the equations in the structural model so that each equation has only one endogenous variable (on its left hand side) and this endogenous variable is expressed as a function of only exogenous variables multiplied by functions of the structural equation parameters on its right hand side. The rank condition is met if it is possible to uniquely recover the structural equation parameters from estimates of the reduced form parameters, which will be possible if the matrix that represents the transformation from the reduced from coefficients to the structural coefficients is of full rank.

In a case where the endogenous variables in the structural model are latent constructs, the structural equation model will not be identified even if the rank and order conditions are met unless other constraints are imposed on model parameters. The problem that the measurement model induces is that the latent variables have an arbitrary scale. To identify the model the scale of the latent variables has to be fixed in advance of estimation. In the estimations used for this study, we use Stata's default identification restrictions, which are the following (StataCorp LP, 2011, p. p. 28):

1) All latent variables, here for the constructs in the model, have a mean of zero.
2) All latent endogenous variables have an intercept of zero.
3) The coefficient on the path from each latent variable to its first observed endogenous variable is constrained to be 1.0.

Restrictions 1 and 3 apply to the latent variable and the measurement model that follows.

Appendix J

An Alternate Mediation Analysis Model Examining ROPAS, SOCS and SOID Factors from Study Two

To test the probable mediator role of SOID, a mediation analysis method was used, Baron and Kenny (1986). To begin with, there must be significant relations among independent, dependent, and mediator variables as prerequisites of a mediation analysis. Here, SOCS is the dependent variable, ROPAS is the independent variable, and it is hypothesized that the effect of ROPAS on SOCS will be mediated by O_SOC. As depicted in the correlation matrix in Table J1, there is a significant correlation between a user's SOCS, SOID, and ROPAS scores, with an especially high correlation between SOCS and SOID. Beyond the significant correlation with ROPAS and SOID, SOCS also has a significant positive correlation with all other subscales of the BCSS and O_SOC. Consequently, all related constructs and demographic variables (gender, age, and education) were entered into the model as control variables.

J Table 1 Correlations among construct scales

Scale average	CONT	PRIM	EFFE	DIAL	SOCS	SOID	EFFO	CRED	ROPAS	O_SOC
1.CON	1.000									
2. PRIM	0.338$^+$	1.000								
3. EFFE	0.313$^+$	0.625$^+$	1.000							
4. DIAL	0.216$^+$	0.641$^+$	0.592$^+$	1.000						
5. SOCS	0.119**	0.339$^+$	0.354$^+$	0.407$^+$	1.000					
6. SOID	0.126**	0.291$^+$	0.356$^+$	0.403$^+$	0.745$^+$	1.000				
7. EFFO	0.452$^+$	0.417$^+$	0.318$^+$	0.362$^+$	0.124**	0.117**	1.000			
8. CRED	0.394$^+$	0.501$^+$	0.371$^+$	0.425$^+$	0.228$^+$	0.152$^+$	0.483$^+$	1.000		
9. ROPAS	0.128**	0.157$^+$	0.184$^+$	0.174$^+$	0.293$^+$	0.333$^+$	0.106*	0.147$^+$	1.000	
10. O_SOC	0.117**	0.119**	0.050$^+$	0.073	0.130**	0.195$^+$	0.002	0.049	0.161$^+$	1.000

*Note: *p < 0.05, **p < 0.01, $^+$p <0 .001*

According to Baron and Kenny's (1986) mediation model, there are three criteria for mediation: (1) the predictor variable (ROPAS) must significantly predict the outcome variable (SOCS); (2) the predictor variable (ROPAS) must significantly predict the mediator (SOID); and (3) the predictor variable must predict the outcome variable less strongly after the mediator added to the model.

The regression model that shows the significant effect of the ROPAS on SOCS scores in Table J2 reproduced here from Chapter 4 of the thesis satisfies the first criterion.

J Table 2 Regression Estimates for SOCS average and SOID average regressed on ROPAS average

	Coeff.	Std. Err.	t	P>|t|	95% LCL	95%UCL
SOCS average						
ROPAS average	0.165	0.024	6.97	0.000	0.119	0.212
Constant	2.324	0.094	24.67	0.000	2.139	2.509
SOID average						
ROPAS average	0.187	0.023	8.05	0.000	0.141	0.232
Constant	2.126	0.092	23.05	0.000	1.945	2.308

The second criterion was tested via a regression model in which SOID score is treated as outcome variable and ROPAS is treated as predictor. Again all other constructs were added into the model as controls and in addition to this SOCS also added as a control into the model because of the high positive correlation with SOID score. Results of the regression are provided in Table J3. As can be seen in this table, ROPAS has a significant effect on SOID scores, B = 0.653, SE = 0.034, p < 0.001. Other than ROPAS, SOCS, EFFE, DIAL, CRED, O_SOC also has an effect on it, B = 0.117, SE = 0.041, p = 0.004. Although the reason for a negative relationship between CRED and SOID here is not obvious the important point is that the results satisfy the second criteria of the mediation analysis.

J Table 3 Regression Estimates for SOID average regressed on ROPAS average

Scale Averages	Coef.	Std. Err.	T	P>|t|	95% LCL	95% UCL	F	df	R^2
Gender	-0.018	0.086	-0.204	0.838	-0.186	0.151	66.88*	11,509	0.534
Age	0.001	0.003	0.534	0.594	-0.004	0.006			
Education	-0.005	0.082	-0.066	0.947	-0.167	0.156			
SOCS	0.653	0.034	19.005	0.000	0.585	0.720			
PRIM	-0.068	0.057	-1.208	0.228	-0.179	0.043			
EFFE	0.076	0.035	2.178	0.030	0.007	0.144			
DIAL	0.152	0.048	3.147	0.002	0.057	0.246			
CRED	-0.135	0.068	-1.988	0.047	-0.269	-0.002			
EFFO	0.018	0.043	0.424	0.671	-0.066	0.102			
O_SOC	0.117	0.041	2.867	0.004	0.037	0.198			
ROPAS	0.061	0.018	3.324	0.001	0.025	0.098			
Constant	0.241	0.261	0.924	0.356	-0.272	0.754			

Note. $p<0.001$

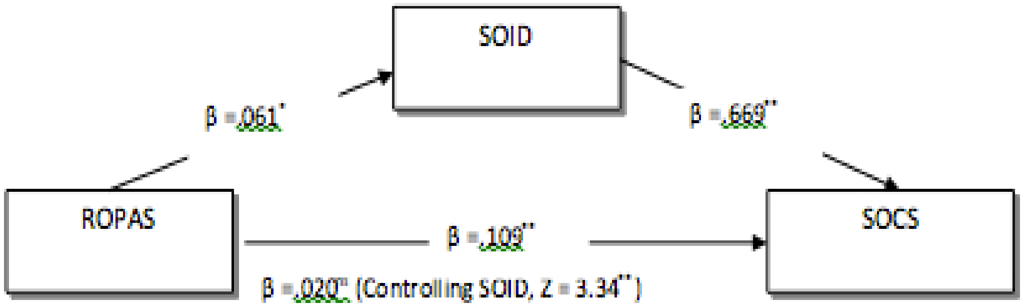
To test the third criterion of mediation analysis, two sets of regression analysis were estimated. In the first model shown as Set 1 in Table J4, predictor variable and control variables are entered into a model in which SOCS is the outcome variable. In the second step, Set 2 in Table J3, SOID is added to the model as a mediator.

J Table 4 Regression Estimates for SOCS average regressed on SOID and other related constructs

	Scale Averages	Coef.	Std. Err.	t	P>|t|	95% LCL	95% UCL	F	df	R^2
Set 1	Gender	-0.343	0.117	-2.942	0.003	-0.572	-0114	20.09*	10,510	0.276
	Age	-0.010	0.003	-2.747	0.006	-0.016	-0.003			
	Educ.	0.322	0.116	2.773	0.006	0.094	0.550			
	PRIM	0.066	0.072	0.915	0.361	-0.076	0.208			
	EFFE	0.117	0.054	2.168	0.031	0.011	0.223			
	DIAL	0.326	0.065	4.972	0.000	0.197	0.454			
	CRED	0.102	0.081	1.258	0.209	-0.058	0.262			
	EFFO	-0.126	0.052	-2.417	0.016	-0.229	-0.024			
	O_SOC	0.067	0.058	1.154	0.249	-0.047	0.182			
	ROPAS	0.109	0.025	4.343	0.000	0.060	0.158			
	Const.	1.052	0.360	2.922	0.004	0.345	1.760			
Set 2	Gender	-0.182	0.088	-2.067	0.039	-0.354	-0.009	77.39*	11,509	0.592
	Age	-0.006	0.003	-2.338	0.020	-0.012	-0.001			
	Educ.	0.185	0.090	2.045	0.041	0.007	0.363			
	PRIM	0.083	0.054	1.540	0.124	-0.023	0.186			
	EFFE	0.015	0.035	0.435	0.664	-0.054	0.085			
	DIAL	0.082	0.050	1.654	0.099	-0.015	0.179			
	CRED	0.148	0.071	2.085	0.038	0.009	0.288			
	EFFO	-0.083	0.043	-1.937	0.053	-0.168	0.001			
	O_SOC	-0.041	0.042	-0.966	0.335	-0.124	0.042			
	ROPAS	0.020	0.019	1.056	0.291	-0.017	0.057			
	SOID	0.669	0.034	19.564	0.000	0.602	0.736			
	Const.	0.431	0.278	1.549	0.122	-0.116	0.978			

Note. $p<0.001$

The results of the regression analysis support the hypothesis in the sense that the significant effect of ROPAS disappears after SOID is added to the model. In fact, the results indicate that SOID fully mediates the relationship between ROPAS and SOCS scores. The hypothesis test recommended by Sobel (1982) also confirms the significant mediator effect of the SOID, $z = 3.340$, $p < 0.001$, as depicted in Figure J1.



J Figure 1 SOID Mediates the Relationship between RPOAS and SOCS

. Results of Sobel test for mediation;*p< 0.01; **p< 0.001

Appendix K

BCSS Scale for Assessing Systems Persuasiveness Characteristics

Table K45 Summary of Model Constructs Used in BCSS Scale for Assessing Systems Persuasiveness Characteristics

Construct	Description	Items	Origin
Primary Task Support (PRIM)	System enablement of users' main objectives in using system. Complex tasks are simplified; progress towards goals aided & reflected.	The system helps me in reaching my goals. The system makes it easier for me to reach my goals.	Self-efficacy theory (Bandura, 1997) Goal-setting theory (Locke & Latham 2002) Person-Artefact-Task (Finneran & Zhang, 2003) Oinas-Kukkonen & Harjumaa (2009)
Dialogue Support (DIAL)	System's various mechanisms for providing user feedback.	The system provides me with appropriate feedback. The system rewards me.	Personal Value Congruence & Feedback (Hosack & Paradice, 2014) Fogg & Nass (1997) Oinas-Kukkonen & Harjumaa (2009)
Perceived Credibility (CRED)	How much the user trusts, believes in and respects the system and its content.	The provided content is professional. Overall I consider the system accurate. The provided content is believable.	Online trust concepts (Corritore et al. 2003) Mechanics of trust (Riegelsberger,Sasse & McCarthy, 2005) Wathern & Burkell (2002)
Social Support (SOCS)	How the system motivates users by leveraging social influence and provides support. Comprises elements of a) social comparison, b) normative influence, c) social facilitation, d) cooperation, e) competition, and f) recognition.	The system helps me by enabling me to connect with like minds who share interests. The system makes it easier for me to reach out and connect to similar others. The system enables same to compare myself to others. The system recognises my goal completions. The system enables me to compete against similar others as well as work collaboratively with them.	Butler (2001) Chiu et al. (2006) Shin (2013) Stibe (2014) Social identity (Tajfel 1974) Group cohesion (e.g. Yoo & Alavi 2001) (Ma & Agarwal 2007)
Social Identification (SOID)	Identifying with other users of the system through shared attributes	I don't care about other users of the system (reverse item). It's easy for me to relate	Social Identity Theory (Turner & Oakes, 1986). Self,Identity & Identity Formation Cinoğlu &

Construct	Description	Items	Origin
		to other user's experiences.	Arıkan (2012). Oinas-Kukkonen & Harjumaa (2009)
Perceived Effort (EFFO)	How hard or otherwise the user finds the system to use.	Using the system is straightforward for me. Using the system does not require a lot of effort from me.	Technology Acceptance Model (Davis, 1989) (Davis &Venkatesh 2000) UT-AUT2 (Venkatesh et al. 2003,2012)
Perceived effectiveness (EFFE)	How useful the systems in satisfaction of user usage goals and accrual of benefits.	My chances of exercising regularly improve by using the system. Using the system has an effect on my exercise behaviour.	Modified from UT-AUT2 (Venkatesh et al. 2003,2012)
Continuance intention (CONT)	The user's intention to keep using the system in the future.	I am going to continue to use the system. I am not going to use the system from now on. Reverse item.	Bhattacherjee (2001), Ortiz de Guinea and Markus (2009)

Appendix L

Implications for Design

Some of the findings from this study may have design implications for vendors of exercise apps including Suunto; particularly in relation to encouraging regular use of the systems for exercise management. Some of these design features have been implemented in apps such as melonhealth.com and the Dashboard in Apple HealthKit. To demonstrate how research findings such as those identified in this thesis can operationalised a demonstration web app for exercise physiologists to treat patients using exercise interventions and clinical device data can be found at https://dialog.fit.

The tendency for those users that followed the activities of others using the system to engage in more frequent system usage presents an opportunity for vendors to make “follow” features explicit and persistent across screens, pages and interface cues used for navigation and user action. Such a facility should also preserve the privacy provisions for data disclosure as determined by regulatory authorities. An operationalised example can be found in this demonstration system online https://dialog.fit/people; Copyright© D.L.Foy & C.Broadbear (2016).

The proclivity of those users that publish their uploaded exercise sessions to Twitter may encourage designers to have a publish to social media function should be prominent in the app user interface at that point where exercise is uploaded. The availability of the Twitter API from twitter.com ensures the publication of data streams including standard user interface icons. This social media sharing feature was found to be of more importance for the less fit members of the user population analysed and positively associated with persistent use of the exercise app. An operationalised example of such a design feature can be seen online athttps://dialog.fit/track; Copyright© D.L.Foy & C.Broadbear (2016).

The tendency for a majority of the Suunto study users to use the system's *thumbs* function to signify self-affirmative contentment with uploaded exercise sessions lends itself to the application of visible cues that tie to system login. Given the positive association between self-affirmation and exercise adherence providing the user with the ability to indicate how they feel about their exercise efforts may be a behavioural design device for improving persistent use of the technology for exercise. In dialog.fit this is reflected in the "how do you feel about exercise" cue displayed when the user next logs-into the system and again across text and email notifications to peer support groups that trigger when members achieve or exceed planned exercise targets. . An operationalised example of such a design feature can be seen at https://dialog.fit ; Copyright© D.L. Foy & C.Broadbear (2016) for registered users to access only in subsequent log-ins.

The finding that those who demonstrate strong relatedness to others in offline exercise activities tend to make more use of online social connectedness features could persuade designers to programmatically integrate a simple scale device in the user interface to determine the relative level of related needs for each individual. This technique could corral users to alternate user experiences more suited to their preference for these levels. This would mean those with low relatedness needs would have the option of not having social connectedness features included in their UI.

Appendix M

Generalising the Models Used

For mobile and wearable technologies to improve the wellbeing of people, it is important that persuasive design principles are understood and appropriately applied, (Matthews, Win, Oinas-Kukkonen, & Freeman, 2016). This means providing methods and techniques that validate design decisions based on real world data. Exactly. The thesis has revealed the characteristics of a free-living population of activity tracking systems users, validated existing measurement devices to ascertain the level and completeness of persuasive system design factors, created new structural models and measurement scales to identify the influence of social support and its identification in encouraging continued use of an activity tracking system.

Using factorial analysis, consistent with BCSS theory that explored persuasiveness of software-based technologies for effective weight-loss interventions and alcohol cessation work. It was proven that *a system's effectiveness is strongly driven by its ability to enable users to complete primary tasks and the effort required to do this is perceived to be not insurmountable by the user*. There is no reason to think that this finding could not be generalized to a symptomatic population using the activity tracking system that was used here or similar systems from alternate vendors. To ascertain the relative effectiveness of other systems would require application of the same or similar structural modeling methods.

Structural Equation Modeling (SEM) and mediation analysis identified the effects of ROPAS scores on the SOCS and SOID social design factors of BCSS such that ROPAS results predict SOCS scores although SOID fully mediates the relationship between ROPAS and SOCS scores. In practical terms this means those individuals that actively engage with others during exercise will tend to make full use of the social support functions of an activity tracking system, particularly if they feel a social identification with the system itself. There is no reason to not suppose this finding wouldn't translate reasonably well with symptomatic users of this or similar activity tracking systems.

The social support functions of activity tracking systems applied to symptomatic populations may require particular attention from design teams given the extensive evidence that points to the salience of social and emotional support for successful interventions including self-management in battling chronic conditions, (Strom & Egede, 2012) and (Reblin & Uchino, 2008). If we are to translate the work from this thesis to a clinical setting it's incumbent upon systems designers to ensure clinicians are comfortable with their use and can make use of data integration. Chiauzzi, Rodarte, & DasMahapatra (2015), believe monitoring devices can make difference to health self-management, but the validity and reliability of measurements need to be established. For persuasive systems designs this means including an emphasis on features that improve systems credibility (CRED) for a new audience; clinicians.